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CAPTURING VIDEOS OF TRAINS UNDER AMBIENT LIGHTING CONDITIONS FOR COMPUTER VISION ANALYSIS

BY

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THESIS

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ABSTRACT

Intermodal trains are usually the fastest freight trains in North America. Fuel consumption in these trains is high because of their aerodynamic characteristics. If the loads on these railcars were placed in better configurations, it would be possible to reduce fuel consumption. In order to inspect their trains for their aerodynamic characteristics, Burlington Northern Santa Fe (BNSF) has sponsored a project to build a wayside machine vision (MV) system in Sibley, MO, a busy intermodal freight train route called TRANSCON. Our research group at the Beckman Institute, in collaboration with the Civil Engineering Railroad program, has developed a wayside MV system that captures videos of trains passing by. It consists of various train detection sensors, personal computers, and camera and lighting towers. After the video data is collected, it is analyzed using the Train Monitoring System (TMS) and Train Scoring System (TSS) algorithms. Finally, each car in the train is given an aerodynamic score. Currently, the system is functional in analyzing videos that have been acquired in daylight.

This work analyzes the requirements of the TMS algorithm, improves TMS performance on daytime trains, and reports the design of a lighting system that will be used to provide sufficient lighting for the scene at night or when there is not enough daylight. This work investigates the causes of the problems with exposure, and uses non-realtime adjustment of the camera to acquire properly exposed videos. The results show improvement in TMS results. Also discussed is the groundwork done for the lighting sub-system.

To my parents for their love and encouragement.

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CHAPTER 1

INTRODUCTION

1.1 Overview of Computer Vision

Computer vision (CV) deals with acquiring, processing, analyzing, and understanding the content of images. CV methods are used to make useful decisions about physical objects and/or scenes based on these captured images [1]. A typical CV system consists of a radiation source, camera optics, sensor, processing unit, and actors. The radiation source illuminates the scene and the camera optics collect the light scattered and radiated from the objects in a scene. The sensor then converts the incoming light into a meaningful image of the scene. The processing unit processes the image to extract meaningful features which are used for the task that the CV system is designed to accomplish. Based on the output of the processing unit, the actors, usually software, perform certain actions [2]. Applications of CV include mobile robot navigation, military target verification, human computer interaction and medical image analysis, to name a few [3].

Machine vision (MV) is the use of CV techniques in industry and manufacturing. CV is concerned with making computers understand what is perceived visually while MV is an engineering discipline that uses digital input/output devices and computer networks to control other equipment. A common application of MV is the inspection of manufactured goods such as semiconductor chips, automobiles, food, etc. Hence, MV systems, like CV systems, often contain radiation sources, digital cameras, smart cameras, and image processing software to perform these inspection tasks.

The use of MV techniques for the inspection of train components is a recent advancement [4]-[6]. Intermodal trains are usually the fastest freight trains in North America. Fuel consumption in these trains is high because of their aerodynamic characteristics. If the loads on these railcars were placed in more aerodynamic configurations, it would be possible to reduce fuel consumption. In order to inspect their trains for their aerodynamic characteristics, Burlington Northern Santa Fe (BNSF) has sponsored a project to build a wayside MV system in Sibley, MO, a busy intermodal freight train route called TRANSCON. Our research group has developed a wayside machine vision system that captures videos of passing trains. It consists of various train detection sensors, personal computers, and camera and lighting towers. After the video data is collected, it is analyzed using the Train Monitoring System (TMS) and Train Scoring System (TSS) algorithms. Finally, each car is inspected and scored for how it was loaded and the train is given an aerodynamic score. Currently, the system is functional in analyzing videos that have been acquired in daylight.

My role in this project has been to analyze the requirements of the TMS algorithm, improve TMS's performance on daytime trains, and design a lighting system that will be used to provide sufficient lighting for the scene at nighttime or when there is not enough daylight. Figure 1.1 shows the flow chart of the existing system. According to the flow chart, all of the work described in this thesis would fall under the first three blocks: incoming train triggers system, adjust camera aperture, and start capturing train video. It is here that the exposure settings, etc., are initialized in order to successfully capture a video of the passing train.

1.2 Overview of the Thesis

This thesis consists of two parts. The first part deals with acquiring properly exposed videos and the second with the lighting design for nighttime. In Chapter 2, we discuss

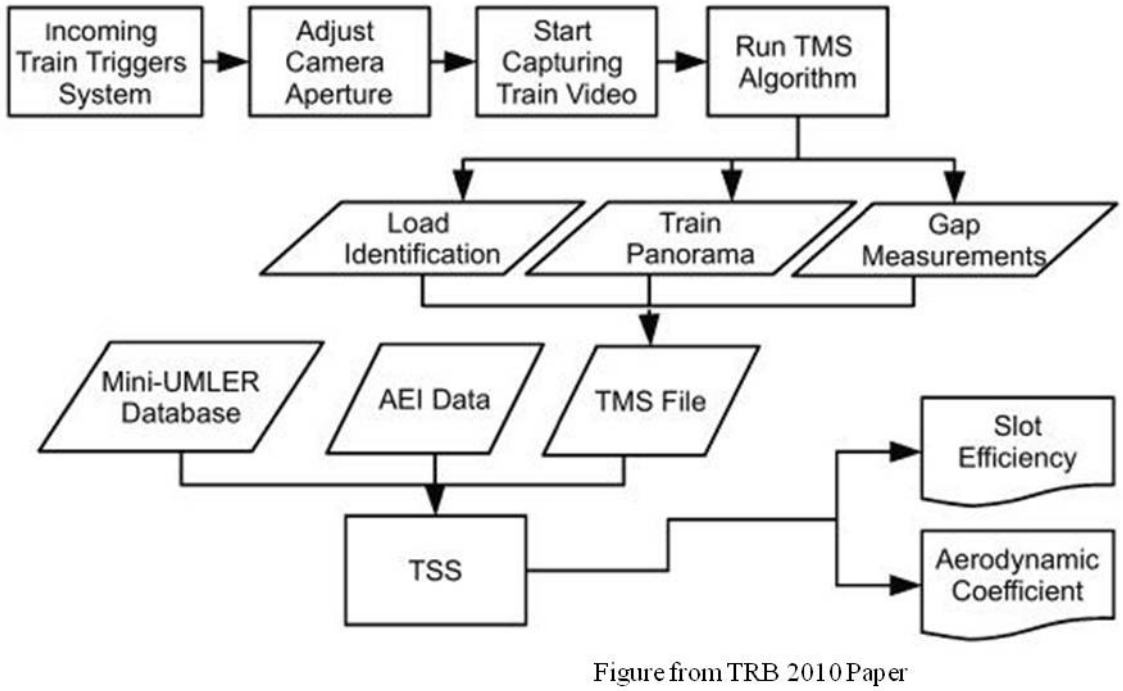


Figure 1.1: Flow chart of the machine vision automation system and sub-systems [7]

the background for the project and set up the problem. Chapter 3 investigates the causes of the problems with exposure, and explores an initial approach to solving the same. We discuss our approach to acquiring properly exposed videos in Chapter 4. The results are discussed in Chapter 5. Finally, in Chapter 6, we discuss the groundwork we have done for the lighting sub-system.

CHAPTER 2

PROJECT BACKGROUND

2.1 Motivation for the Project

A large number of intermodal (IM) freight trains travel on the North American railroad network. These trains typically consist of 100-125 railcars that are each 35-40 meters long. These railcars are loaded with containers of various sizes or trailers (the detachable rear part of a truck, often seen on highways). These trains, which are thus up to or over 3 miles long, move at speeds of 75-80 mph. The aerodynamic resistance of these trains is high due to these high speeds and the flow of air through the gaps between containers. This increases fuel consumption and thereby operation costs.

To reduce fuel costs, Lai [8] investigated the impact of container size on fuel consumption. He concluded that placing small containers on large railcars results in high aerodynamic resistance. He further proposed that analyzing the gap lengths between consecutive containers could yield a good metric for establishing the link between loading pattern and fuel consumption. This analysis could serve as a feedback at various loading centers to improve the loading pattern and reduce fuel consumption in the future.

To accomplish this analysis in a time and cost-efficient manner, it is important to automate the measurement of container gap lengths and loading efficiency. Our research group in the Computer Vision and Robotics Laboratory (CVRL) has been working towards this objective by developing a MV system. One of the students in our group, Avinash Kumar, was involved in developing this system. The following

sections will describe this system.

2.2 System at Sibley, MO

BNSF and the University of Illinois at Urbana-Champaign (UIUC) are developing a fully automated wayside system along BNSF's southern TRANSCON in Sibley, MO. Approximately 40-50 trains that travel between Chicago and Los Angeles pass by this site each day. Hence, analyzing the loading pattern of trains that pass through Sibley and making the required adjustments would help reduce the fuel costs during the long journey to Los Angeles. Figure 2.1 shows a map of the site.

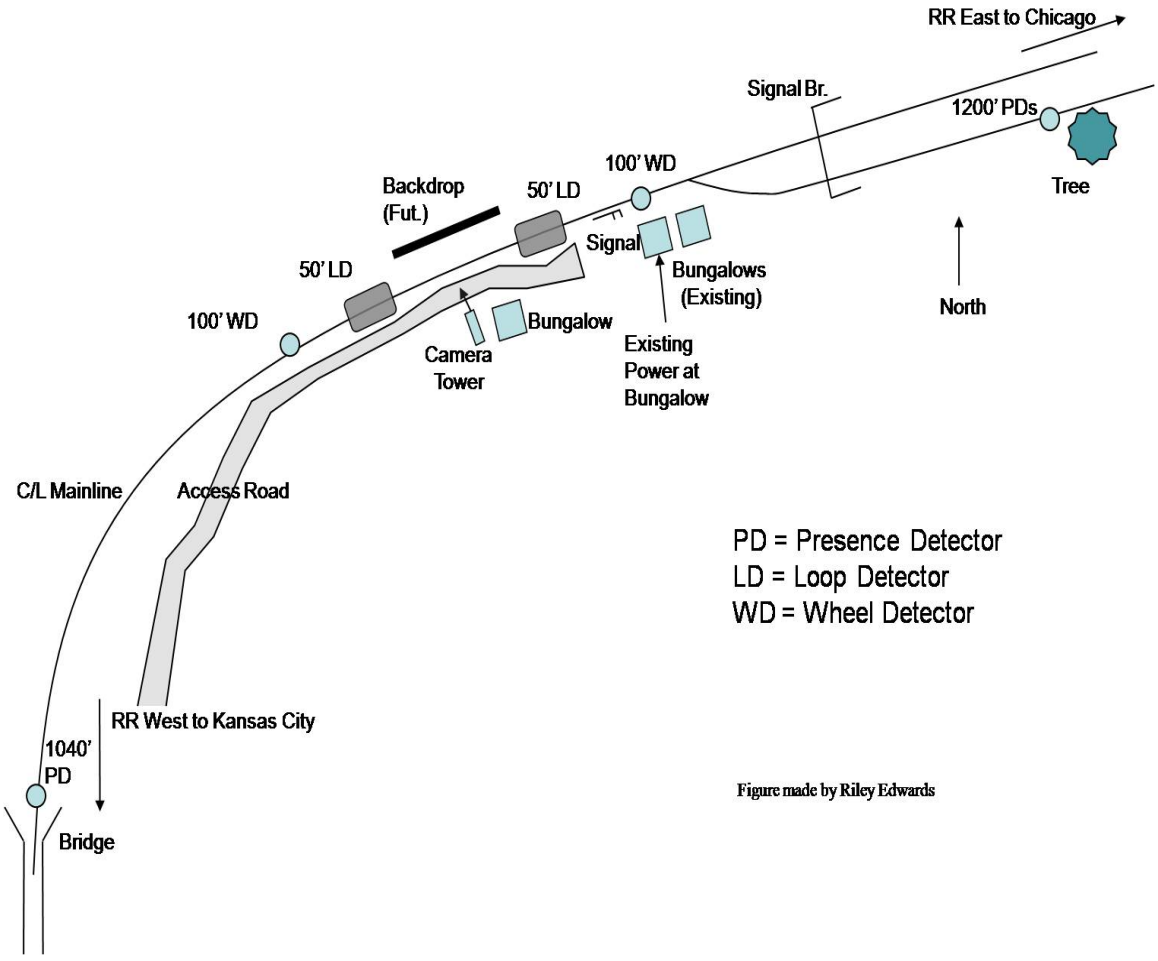


Figure 2.1: Map of site at Sibley, MO

As shown in Figures 2.1 and 2.2, the MV system consists of a camera tower, an automatic equipment reader (AEI), detector electronics, a bungalow that houses the computers, and a reference checkerboard target that is used to adjust the exposure of the camera. There are three types of train detectors that have been installed on the tracks. The outermost are called presence detectors (PD), and use microwave technology to detect approaching trains. They send wireless signals to the detector electronics inside the equipment bungalow when a train is detected. When these detectors are triggered, the camera's exposure is adjusted using the checkerboard target.

Next, are the resonant-type wheel detectors (WD). When the train passes over the WD, a pulse is sent to the computer in the bungalow and video acquisition is started. The camera used at the site is a charge-coupled device (CCD) camera. To understand how a CCD camera operates, and the properties of the DragonFly2 camera being used, please refer to Appendix A. When the incoming train triggers the MV system, the camera's exposure is adjusted using the checkerboard target that is in front of the camera. This is done by setting the exposure and iris settings of the camera on auto mode for 5 seconds. During these 5 seconds, the scene that the camera is looking at consists entirely of the region of interest (ROI) in the checkerboard target. We expect the exposure and iris settings to converge to an appropriate value in these 5 seconds. Auto mode is then turned off. The values that exposure and iris converged to are then used as the settings during the entire acquisition of the video. At this point, the dimensions of the image are expanded to 640 by 480 pixels. We assume that the values set for the camera properties based on the checkerboard target would be appropriate for the entire scene also. The video is then captured at 30 frames per second. The shutter speed is set at 4.25 milliseconds. This value was empirically found to have minimal motion blur.

Finally, inductive loop detectors (LD) have been placed on the tracks in front of

the camera. These detectors send a continuous signal if there is a train over them. These detectors are used to determine if the train has stopped in front of the camera. The other detectors send signals only when the train is moving.

Figure 2.2: Southern view of the machine vision system at Sibley, MO. Shown from left to right, the AEI reader, equipment bungalow, camera tower, communication tower and exposure target.

An automation system has been developed to detect trains, acquire videos, and perform MV analysis of the video. After the video of the train has been acquired, the automation software triggers the software for analyzing and scoring the train and transfers the results to BNSF directly [9].

2.3 Train Monitoring System

This section will discuss in detail the Train Monitoring System (TMS) that is used to process an IM train video. CV and image processing techniques are used to obtain gap lengths between the loads on the train. Figure 2.3 shows the overall flow of the TMS algorithm, starting from video acquisition to the calculation of gap lengths.

A DragonFly2 camera from Point Grey Research is used for video acquisition whenever a train passes by. The camera is set to capture at a frame rate of 30 frames per

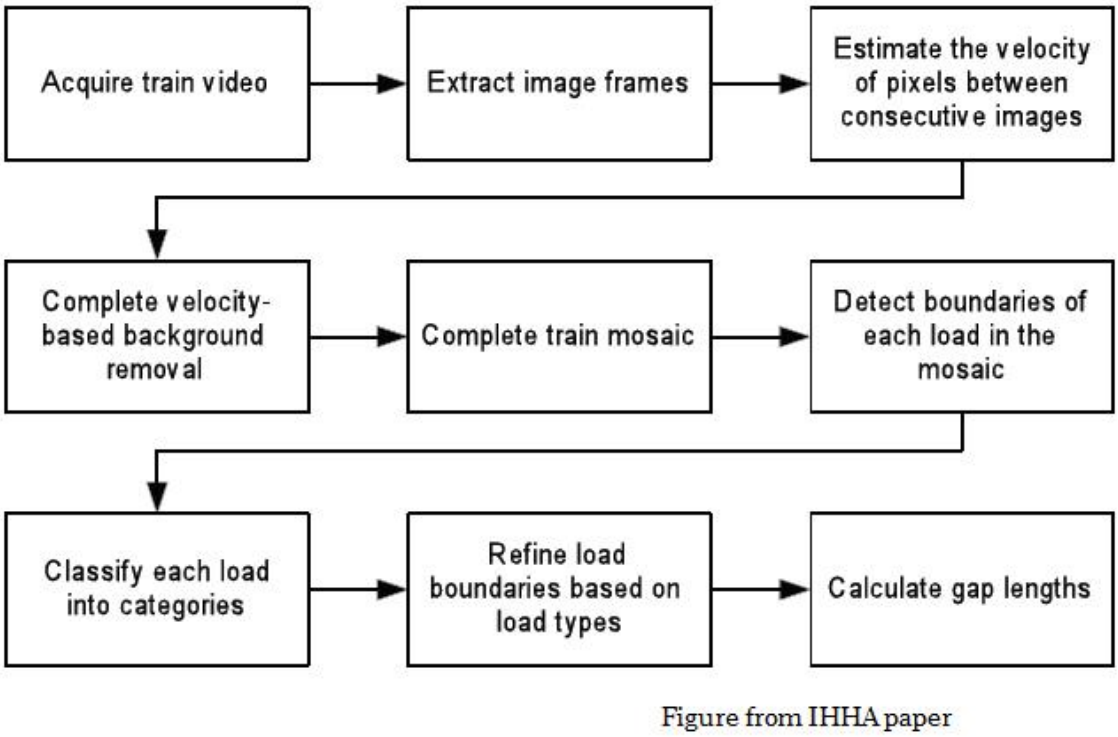

Acquire train video
Extract image frames
Estimate the velocity of pixels between consecutive images
Complete velocity-based background removal
Complete train mosaic
Detect boundaries of each load in the mosaic
Classify each load into categories
Refine load boundaries based on load types
Calculate gap lengths
Figure from IHHA paper

Figure 2.3: Flow of the TMS algorithm [9]

second (fps), and each frame is of size 640 by 480 pixels. The beginning of the video contains only the plain background, which consists of the sky, trees, other scenery, etc. After a short period of time, when the train enters the field of view of the camera, the video captures the IM train also as it passes in front of the camera. Video acquisition is stopped automatically after the train has completely passed by. Figure 2.4 shows a frame from the video that contains only the background and one that also contains the train.

TMS's first task is train identification and segmentation (background removal) in each frame. This is achieved by calculating the normalized cross correlation between consecutive frames. There are several classical segmentation techniques in image processing. A comparative evaluation is given in Appendix B.

Segmentation is performed in the following manner:

1. TMS averages the RGB values of each pixel in each frame to obtain a single

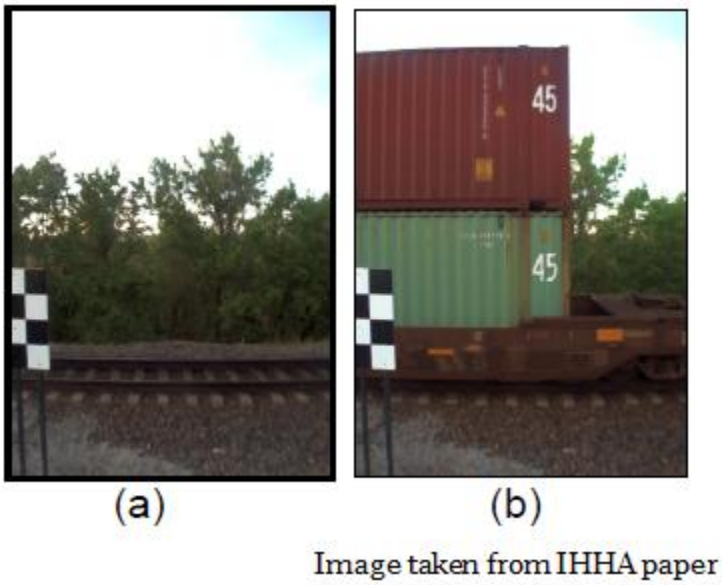


Figure 2.4: (a) Plain background recorded at the beginning of the video, (b) Train recorded when in the field of view of the camera [9]

value. Hence, each frame is converted to a gray-scale image.

2. We first compute the amount of movement of pixels in an image between consecutive frames. The movement can be measured accurately because the intensity of pixels between consecutive frames will not change much. The pixel movement is just the difference between the locations of the same pixel in consecutive frames. Based on the fact that the train moves faster than objects in the background, high velocity pixels should belong to the train. Thus, pixels with high velocities are classified as foreground.

3. We next attempt to remove the background. The search for the train starts from the second frame, and the initial background estimate is calculated from the first frame, which always contains only the background. After identifying the train in each frame, the estimate for the background is always updated to account for minor changes in the scene (for example, passing clouds, trees swaying in the wind, etc.).

4. Next, the pixel velocity is computed. For this, we define I_c as the current frame, for which pixel velocity needs to be computed. Then, let I_p and I_n denote the previous and next frames to the current frame, respectively. I_{bg} denotes the current background estimate. The initial train velocity estimate can be calculated by correlating the common parts of the railcar that are visible between consecutive frames. This can be done because we know that part of the train, with or without a load, will always be visible in consecutive frames.

5. Using this initial velocity estimate, v, the regions that are moving with that velocity in I_c are found. In order to do this, a window of size 21 by 41 pixels in I_c is taken at all locations (x, y) and correlated with a window of the same size in I_p at location $(x - v, y)$ and in I_n at location $(x + v, y)$. We only consider the horizontal direction because we know that the train only moves horizontally, and that any vertical motion is negligible.

6. The correlation procedure referred to in the previous step uses normalized cross correlation (NCC). NCC requires the mean pixel intensity of the window to be subtracted from every pixel in the window. This would reduce the effect of lighting changes. All the pixel intensities in the window are normalized so that their sum of squares is 1. At each window at location (x, y) in I_c, the correlation with I_p, NCC_p, the correlation with I_n, NCC_n, and the correlation with I_{bg}, NCC_{bg}, are calculated. NCC_{bg} will be high if the window in I_c belongs to the background.

7. The three NCC values are combined to compute FG_{cost}, the cost for a pixel centered in the window to be part of the foreground.

$$FG_{cost} = \frac{(NCC_p + NCC_n - 2NCC_{bg})}{4}$$

The denominator normalizes FG_{cost} so that the value is between -1 and 1. FG_{cost} will be close to 1 when NCC_p and NCC_n are high and NCC_{bg} is low. When this is the case, the window in I_c will be categorized as foreground. If the window is part of the background and the current estimate of the background is textured (sky with clouds), then both NCC_p and NCC_n would be close to -1. If the window is part of the background and the current estimate of the background is texture-less (clear sky), then both NCC_p and NCC_n would be close to 1. However, in both cases, NCC_{bg} will be close to 1 since the patch in I_c belongs to the background. Based on all these values, FG_{cost} will take on a value between -1 and 0 if the window in I_c belongs to the background.

8. The system then categorizes a pixel as foreground if FG_{cost} is greater than some threshold value, T, and the other pixels as background. $T = .2$ was found, empirically, to yield the highest number of successful results.

9. Pixels belonging to the background are removed from each frame.

The second task performed by TMS is mosaic generation. Mosaic generation involves stitching together consecutive frames. This needs to be performed given the fact that some containers will be split between two consecutive frames. A mosaic image facilitates easier viewing of intermediate TMS results (i.e. segmentation, edge detection, etc.) and calculation of gap lengths. Strips of width v, the velocity of the train, are taken from I_c and used to form the mosaic or panoramic image. This process is continued for all the frames. Using the velocity, v, helps in creating a seamless panorama of the train, avoiding the problem of repeated or missing train parts. This technique is also therefore adaptive to changing train speed between frames. Figure 2.5 shows a portion of the mosaic for an IM train.

The third task in TMS is the detection of outer boundaries of all loads. Outer boundaries on loads occur when a larger container is placed on a smaller one or vice-

Figure 2.5: A portion of an IM train panorama after background removal

versa. The outer boundary would be the edges of the larger container. Additional edge detection algorithms are used to detect the edges of the smaller container. All edges must be detected so that the loads can be classified, and gap length information can be calculated. The gap lengths between loads are computed by simply taking the difference between the vertical boundaries of consecutive loads.

The final task in TMS is load classification. The Train Scoring System's (TSS) ability to accurately produce an aerodynamic score for a train depends on correct load classification information generated by TMS. All loads are first categorized as a single or double stack based on the height. TMS uses the height of single stacks and other known camera parameters to calculate a threshold height. If the top of a stack is below this threshold height, then the load is classified as a single stack. Alternatively, if the top of the stack falls above the threshold height, then the load must either be a double stack or a trailer. If the load is a trailer, then the background will be visible near the bottom. So, TMS tries to find pixels near the bottom that are similar to the background estimate. If it is successful, then the load is classified as a trailer. Otherwise, the load is classified as a double stack. However, a double stack can have three configurations: (a) a small container placed over a longer one, (b) a longer container placed over a smaller one, or (c) two containers of the same length. Since the edge boundaries differ for each of these double stack configurations, gap-lengths will also vary. Hence, TMS further classifies a double stack into one of these three configurations [9]. The size of the containers are then calculated using pixel-to-foot conversion, based on camera parameters and distance between the camera and the track.

Further edges, such as horizontal and inner edges, are detected based on load classification. Based on this edge information, gap-lengths between containers, one of the outputs of TMS, are calculated. TMS has now produced two outputs: gap-length and load classification information. These outputs are fed into TSS, which produces an aerodynamic score for the train. TSS does not use MV or image processing techniques and is described in detail elsewhere [9].

2.4 The Problem

For TSS to properly score a train video, TMS needs to produce accurate gap-length information as input to TSS. The ability of TMS to calculate gap-lengths accurately, in turn, depends critically on the success of the background removal. All subsequent tasks within TMS depend critically upon this task. For proper background removal, TMS must be supplied with a properly acquired video with proper exposure. This will help in correctly distinguishing the loads on the train from the background.

Currently, most of the videos that are captured are exposed properly and pass TMS with fairly good background removal cases. However, there are some cases where the videos that we have captured to date are either under-exposed or over-exposed. In addition, in some videos, the frames get over-exposed over the course of the video, thus leading to either a completely white image or mostly 'washed-out' images of the train. On the other hand, in some videos, the converse occurs; over the course of the video, the frames become under-exposed, leading to frames that are completely black or very dark that it is very hard to identify the train. Certainly, TMS cannot perform well when either kinds of videos are processed. Apart from this, videos that look properly exposed to the eye are still producing problematic TMS results. Hence, the first part of this thesis concentrates on finding a solution to make sure under/over exposed videos are no longer captured, and to solve the fading. This will improve

TMS results for these types of videos. This involves investigations and development of solutions to provide TMS with good videos in order to improve TMS's success rate. In the next chapter, we further elaborate on this problem and we discuss our approach to overcoming these problems in the subsequent two chapters.

CHAPTER 3

INVESTIGATION OF SEGMENTATION ERRORS IN TMS

As stated in Chapter 2, TMS needs properly exposed videos for accurate analysis using MV techniques. This chapter further elaborates on the existing problems with intermediate (segmentation and edge detection) TMS results for videos that look like they are properly exposed and the investigation to find the root cause of these errors.

3.1 Analysis of TMS Results from a Set of Existing Videos

We first look at intermediate TMS results for several videos of trains. These are a set of videos that appear to be properly exposed. However, the TMS results for these videos have several errors. We tabulate the intermediate results of TMS for each train video. As mentioned before, the camera uses a checkerboard target to adjust the exposure settings. It is observed that the color of the target differs in each video, so the color of the target is also recorded in the table. TMS results for 100+ trains are recorded in this table. The entire table can be found in Appendix C.

Figure 3.1 shows an ideal intermediate result from TMS, where the background removal is perfect and all edges of the container have been correctly detected. This leads to correct load classification.

Figure 3.2 shows one of the problems with TMS's intermediate results, a case where there is background under-subtraction. The background (sky) is visible between the two trailers and at the top right of the trailer. These are indicated by red circles on Figure 3.2. Since the background is not subtracted between the two loads, the

edge detection algorithm does not detect the vertical edge on the left-hand side of the trailer. Since both the loads are detected as one unit, the length of the gap between these two loads is missing. Figure 3.3 shows another problem that is commonly found in intermediate TMS results. Background under-subtraction near the top of the containers leads to an inaccurate load classification as a double stack.

Figure 3.4 shows background over-subtraction, where parts of the trailer are subtracted. However, since the background over-subtraction does not occur towards the edges of the trailer, the edges are still identified correctly. Another type of background over-subtraction in containers is due to confusion between background and foreground. This occurs especially when a container is very close to the color of the sky (blue or grey). As a result, TMS over-subtracts on these containers, thus leading to bad results.

Figure 3.1: Ideal TMS result

We investigate the cause of the errors described above. First, we observe that the white squares in the checkerboard target, which is also visible in the videos along with the train, are not white. Since the checkerboard target at the site is used to adjust the settings of the camera, we hypothesize that there might be a link between the exposure of the image (color of the white squares in the checkerboard target) and the segmentation errors described above. To confirm this, we analyze the table in Appendix C to see if there is a correlation between the color of the white squares in

Figure 3.2: Background under-subtraction indicated by the red circles

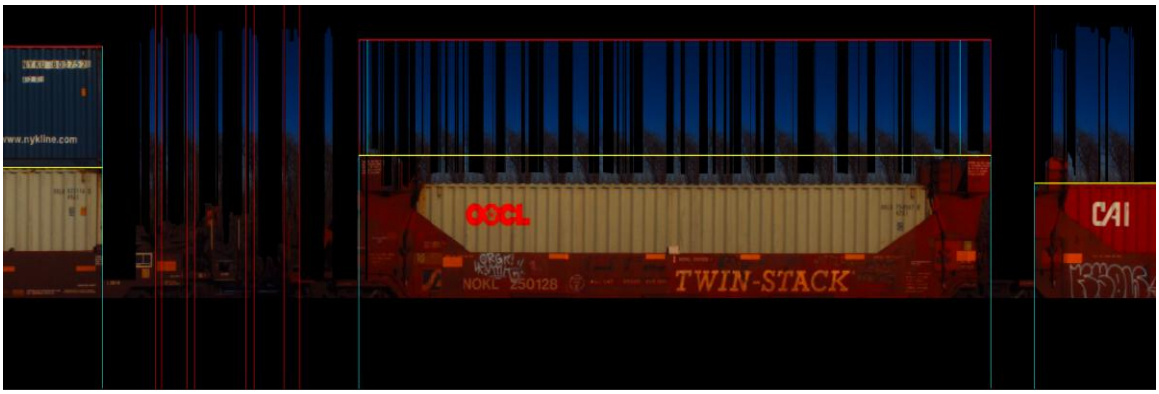


Figure 3.3: Background under subtraction at the top of the single stack leading to incorrect detection of the load as a double stack

the checkerboard target and the problems in the intermediate TMS results recorded. In other words: Is a certain color of the white squares in the checkerboard target associated with a certain type of TMS error? And: Do the white squares in the checkerboard target appear to be a certain color at a particular time of the day? Our analysis shows that there is no such correlation. In fact, there are cases when TMS yields perfect intermediate results when the white squares in the checkerboard target are non-white.

We now turn to analyzing the intensity of the white and black squares in the checkerboard target, and attempt to find a correlation between that and the intermediate TMS results. For this purpose, we follow the outlined procedure:

1. A software called VirtualDub is used to convert the videos into frames.

Figure 3.4: Background over-subtraction, where parts of the container have been subtracted

2. We collect the first frame of each video, which corresponds to the plain background that is utilized in segmentation.

3. We write MATLAB code to convert these color images to gray-scale and then extract a white and black square from the region of interest (ROI) of the checkerboard target in each image.

4. We calculate the average of all pixel values for each of these white and black squares. Please refer to Appendix D for the code.

Figures 3.5 and 3.6 show a plot of these average intensities. The horizontal axis represents each train video and the vertical axis denotes the average intensity of the square in the checkerboard target from that particular train video. We mark certain train videos with an 'O' on the graphs, indicating that TMS over subtracts the background. Some train videos are marked with an 'U', which signifies that TMS under subtracts the background in that video. A few train videos are marked with 'O,M,' which means that background over-subtraction and mosaicking errors are present. We notice that mosaicking errors occur along with background over-subtraction errors.

These graphs show that no clear relationship exists between the average intensity of a white and black square on the checkerboard target and the performance of TMS

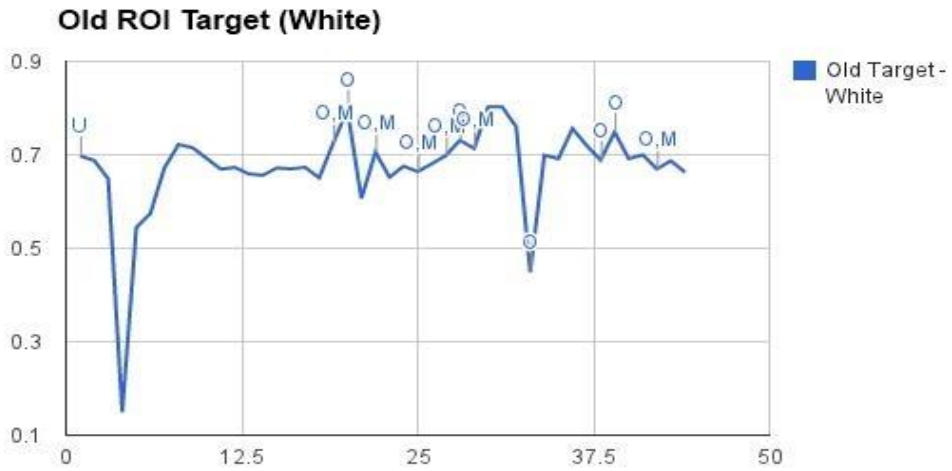


Figure 3.5: Average intensity of the white square in the target. Horizontal axis represents the train and the vertical axis represents the average intensity of the white square.

on that particular train video. However, during this investigation, we make another observation. The average pixel intensity of the white squares is lower than expected. Figure 3.5 shows that all the average intensities recorded are below 0.9. This suggests that although these videos look properly exposed, they are darker than what TMS would need to perform well. It is important to keep in mind that the ROI used to acquire these videos comprises of four squares in total, with 2 black and white squares each. Our next hypothesis is that this ROI is too bright, and thus leads the camera to choose values for its exposure properties such that the videos are darker, from TMS's perspective. In the next section, we attempt to brighten the videos.

3.2 Change of the Region of Interest

In order to brighten the videos, we change the ROI so that it comprises of three black squares and one white square. Since there is more black than white in the ROI, the camera should now adjust its parameters to brighten the video. Videos captured starting from January 2012 use the new ROI, as shown in Figure 3.7.

After 2-3 months of video collection, we repeat the process of analyzing these videos.

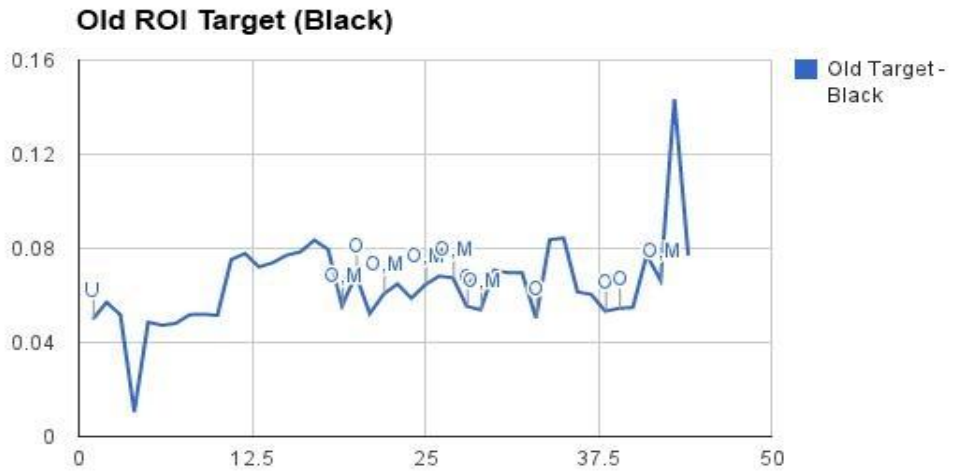


Figure 3.6: Average intensity of the black square in the target. Horizontal axis represents the train and the vertical axis represents the average intensity of the black square.

Figure 3.7: New ROI on the checkerboard target indicated by red box

We first look at the intermediate TMS results and tabulate any errors in the same table in Appendix C. We notice the same problems as described above in these new videos. We then calculate the average intensities of a black and white square in the new ROI, similar to the method used with the old ROI. Please refer to Appendix D for the MATLAB code. We check that there is indeed a boost in the brightness as hypothesized when changing the ROI. Figures 3.8 and 3.9 show a plot of the two sets of average intensities with their respective medians. The median is graphed to see if there is an overall increase in the brightness as expected. Also, the median is immune to outlier data values, unlike the mean.

Figures 3.8 and 3.9 show that the increase in the proportion of the black squares to white squares in the ROI has indeed brightened the videos. The median of the average intensities of the white and black squares from the new ROI is higher than

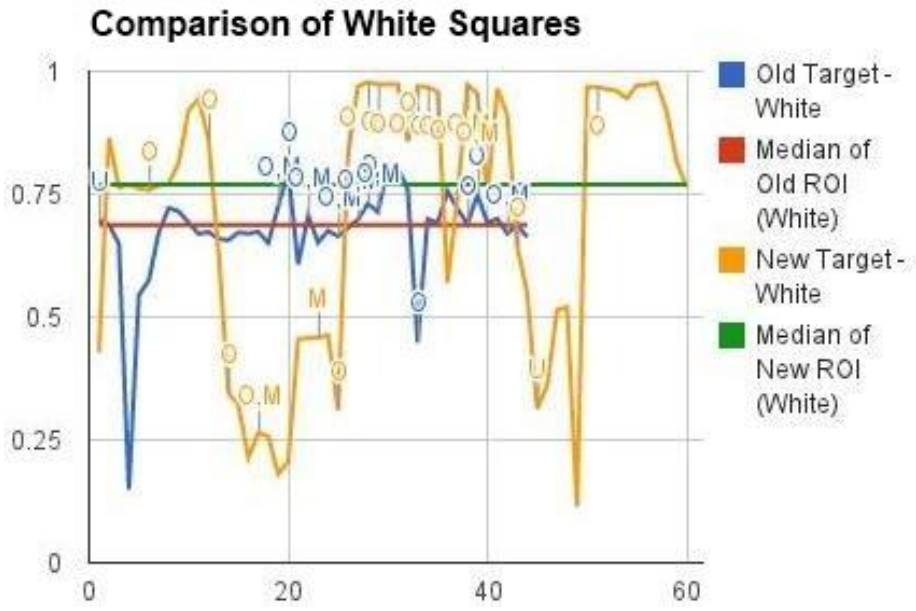


Figure 3.8: Average intensity of the white square in the target with old and new ROI's. Horizontal axis represents the different trains and the vertical axis represents the average intensity of the white square.

the median of the white and black squares from the old ROI. Figures 3.10 and 3.11 show individual graphs of the average intensities of the white and black squares from the new ROI. Again, some train videos are marked with 'O,' 'O,M,' and 'U,' similar to the graphs in Figures 3.5 and 3.6.

We infer a few things from this exercise of calculating the average intensities of black and white squares from the ROI. First, the change in ROI has not rectified the problems with intermediate TMS results. Second, we see considerable fluctuation in the average intensities of the white and black squares between trains. Finally, the problems in intermediate TMS results occur generally when the average intensity is above the median value. In other words, when the video is too bright, segmentation errors occur in TMS results. Now that we have formed hypotheses, we set out to find a solution to these problems. Our initial approach is discussed in the following section.

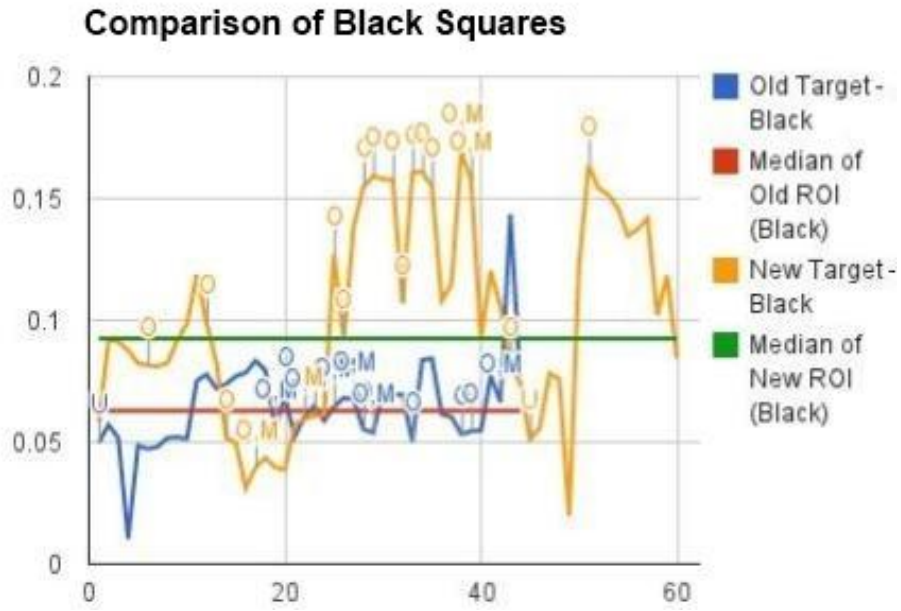


Figure 3.9: Average Intensity of the black square in the target with old and new ROI's. Horizontal axis represents the different trains and the vertical axis represents the average intensity of the black square.

3.3 Initial Approach to Solving the Target Intensity Fluctuation

As mentioned in Chapter 2, the camera uses only the iris and exposure parameters to adjust the exposure of the image each time an incoming train triggers the MV system. From the descriptions of the various camera parameters (Appendix A), clearly several other parameters, namely gamma, saturation, and gain, can be utilized in adjustment. At first, we think that experimenting with these extra parameters could be used to raise or lower the overall image exposure. This in turn could help reduce the fluctuation observed from the graphs of the average intensities of the white and black squares from the ROI. However, these parameters would not be helpful in reducing fluctuation. Saturation as described before only changes the color range of the image. Gain, when put on auto mode, is not adjusted until the iris is fully open. In our case, the iris is never fully open during the daytime. Hence, gain is not a free parameter. Gamma does not have an auto mode, and has to be manually set. The needed value

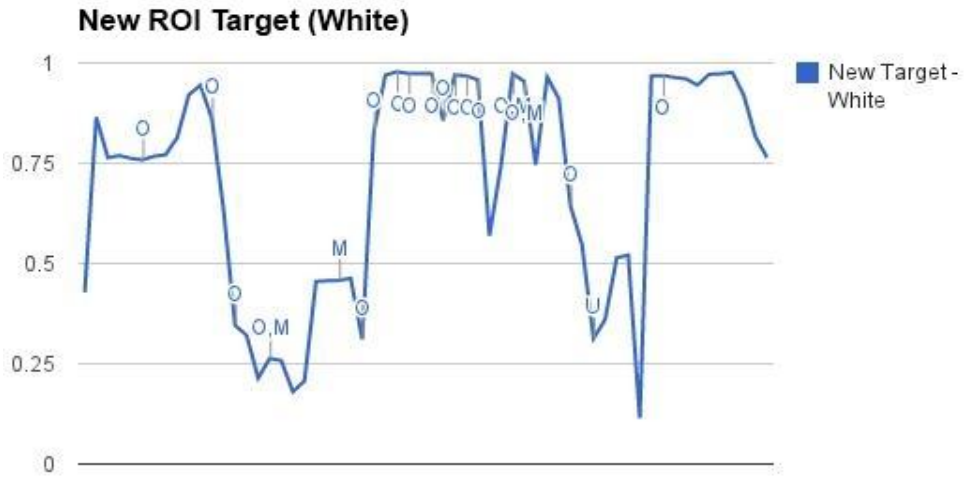


Figure 3.10: Average intensity of the white square in the target. Horizontal axis represents the different trains and the vertical axis represents the average intensity of the white square.

of gamma would vary from time to time, depending on the current scene. This is also not feasible because the whole idea is to automate the entire system. As a result, an alternate approach using the iris and exposure parameters should be implemented to flatten the fluctuation that is observed in the graphs (Figures 3.10 and 3.11). This approach is discussed in Chapter 4.

3.4 Camera Exposure Fading Problem

Apart from the problems observed in intermediate TMS results, we observe a problem in the video acquisition stage itself. Sometimes while acquiring a video, the first few hundred frames have a good image. However, we observed gradual fading to black or white in the following frames. Eventually, the entire frame is either completely black or white for the rest of the video. This type of video is unacceptable as input to TMS. Hence, these videos are deleted. If this problem is solved or at least if the frequency of occurrence is reduced, more daytime videos can be passed through TMS for analysis. We discuss our initial approach to solving this problem in the following section.

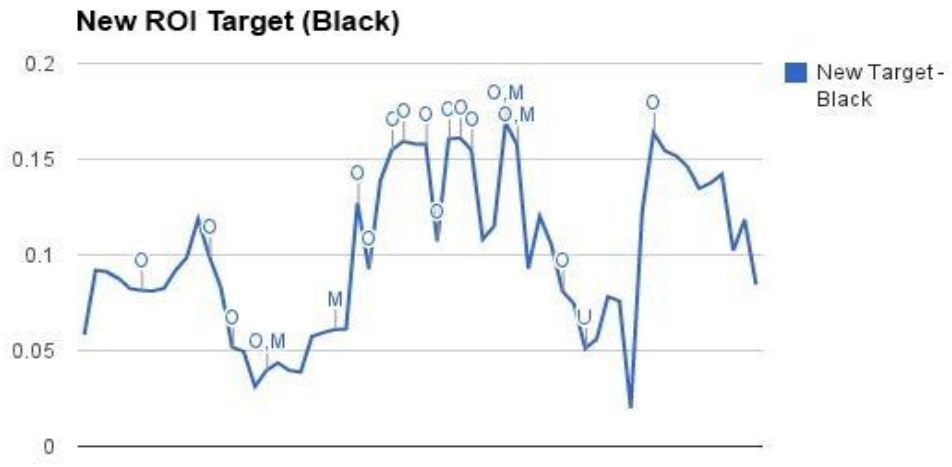


Figure 3.11: Average intensity of the black square in the target. Horizontal axis represents the different trains and the vertical axis represents the average intensity of the black square.

3.5 Initial Approach to Solving the Fading Problem

We found that the fading occurs due to the aperture being open or closed more than needed, leading to white or black frames, respectively. The user manual of the camera states that the iris can be disabled. With this information, we hypothesize that disabling the iris after the 5000 millisecond adjustment time should freeze the iris in place. Hence, this should stop the iris from moving further while the video is being captured, and in return fix the fading observed in the afore mentioned videos.

We implement this idea by writing code to disable the iris after the adjustment of the camera. We enable the iris before adjustment of the camera settings when the next train triggers the system. However, when the iris is disabled, the iris opens completely, leading to a completely white frame. Hence, we conclude that another solution will have to be found to rectify the fading. We also discuss our approach in Chapter 4.

CHAPTER 4

METHODS FOR ACQUIRING PROPERLY EXPOSED VIDEOS

4.1 The Mission

This section is a recapitulation of the goals that need to be achieved by developing a different approach. First, the exposure fading problem needs to be solved. Next, the fluctuation in camera parameters needs to be dampened as much as possible, so that TMS's success rate increases. We hypothesize that if we rectify the exposure fading and dampen the fluctuation in camera parameters, the background removal errors observed in TMS results thus far will be rectified. In the process, we are also determined to find a solution to TMS confusing the foreground with the background.

First, we investigate the cause of the fading, and try to fix it. After that, we attempt to flatten the fluctuation in the target intensity in a way that does not affect the solution to the exposure fading problem.

4.2 Recreation of the Camera Fading Problem

Since no clear cause of the fading could be found, we suspect that the camera at the site in Sibley, MO, might be faulty. In order to prove this correct or incorrect, we need to recreate the fading problem in the lab at UIUC using another identical camera. If it can be recreated, then we can investigate further to find the cause of this fading and develop a way to solve it. If it cannot be recreated in the lab, then we know that the camera at the site is faulty, and can replace it with another unit of

the same model.

We set up another identical camera in the lab, with all parameters set up exactly like those at the site. Exposure and iris are put on auto mode for five seconds (just like at the site) so that the parameters find the ideal values for the current scene. After these five seconds, auto mode is turned off on both exposure and iris. Then, we manually change the iris value alone. We do this because fading to black or white is associated with the size of the aperture. While changing the iris value, we notice that it takes a few seconds for the aperture to actually adjust to the current settings. The fading occurs when the iris starts to adjust to the values set through the software. We change the iris value several times to see if the fading occurs, and it occurs every time.

Hence, this proves that the specific camera unit at the Sibley site is not faulty. The motor that operates to open or close the aperture is taking time to react to the new values that are set through the software. We realized that the iris diameter may in fact be changing even as a train video is being acquired. So, if the value set for the iris property is larger than needed, the aperture opens up too much when the motor starts to adjust the iris. When this operation happens close to when video capturing is to be started, we see the videos starting to gradually fade to white after approximately 100 frames. On the other hand, if the value set for the iris property is smaller than needed, the aperture closes when the motor adjusts it. We see the video fading to black after approximately 100 frames. Now, that we know the cause of the fading, we find a way to solve this problem.

4.3 Approaches to Avoid Fading

We consider possible solutions to avoid fading in videos. The obvious and easiest solution is to replace the lens on the camera with a faster one - one that has a

negligible delay in adjustment. However, we should resort to this option only if there is no other way to avoid fading. Purchasing another lens would add to the expenses for BNSF.

Obviously, the basic technique to avoid fading is to give the system more time (than we are giving now) for it to actually adjust to the new settings. Since we are adjusting the camera settings for every incoming train, this means that an incoming train needs to be detected much earlier than it is now. However, for this to happen, the detectors installed at the site should be moved farther out. This is impossible because there is a bridge on the west-side and a switch leading to multiple tracks on the east-side, as shown in Figure 2.1. The detectors have already been placed at the farthest possible locations on the railway tracks so that the system is given the maximum time to adjust and settle before the train enters the field of view of the camera.

An alternative technique to avoid fading is by adjusting the camera settings frequently. This can be done when a train is not approaching the MV system. The camera's aperture would have enough time to adjust and settle. However, this approach results in a non-realtime adjustment of the camera, meaning that the settings would not be up to date when a train approaches the site. On the other hand, this technique could potentially avoid the fading that is occurring in the videos that are being captured using the dynamic adjustment technique. The ideal frequency of adjustment should be empirically decided. We discuss this technique and the results in the following section.

4.4 Non-Realtime Custom Automation

As mentioned above, this method would not provide realtime adjustment of the exposure, just prior to the arrival of the train, when the video is triggered. However, we

implement this technique based on the assumption that there would not be significant change in the background between the time of adjustment and the time when a train is being recorded. This method does not restrict the time given to the camera for adjustment and settling, and thus should avoid the fading. However, failing to record trains that come in during adjustment is a potential problem, depending on the total time required to set the camera properties on auto mode.

The recording of trains would not be missed for incoming trains when the adjustment is taking place if the adjustment takes only a total of 5 seconds. There are three cases that need to be checked to verify that this method of non-realtime adjustment of the camera will work:

- **Case 1**: Let us say a train approaches the site exactly at the beginning of the adjustment. Then, this is the same case as the dynamic adjustment that is currently in place. The train will be recorded when the train passes over the wheel detectors. However, we may still have fading in the video.

- **Case 2**: Suppose a train approaches the site anytime while the adjustment is taking place. The system will still be ready to start recording when the train passes over the wheel detector.

- **Case 3**: A train will be recorded anyway, when the adjustment is not occurring.

So, in all cases, recording of trains will not be missed.

We implement this technique since we hypothesize that it could solve the fading problem, as long as a train is not recorded in the situation of Case 1 described above. We first use an adjustment frequency of every 30 minutes. This algorithm is then improved upon, based on problems encountered. We discuss the different variations in the following sub-sections. We run each of these variations for 2-3 days, unless stated otherwise.

4.4.1 Variation I: Adjustment Frequency of 30 Minutes

We adjust the camera every 30 minutes (at the hour, and half-hour) by checking if the minutes on the computer clock is either :00 or :30. The camera adjustment technique described in Section 2.2 is used. Since the seconds are not checked, the system repeats the adjustment several times until the minutes of the local time changes. This issue will be addressed in the next variation.

From the videos captured in this variation, we do not observe fading. However, we infer from the videos that an adjustment frequency of 30 minutes is too long of an interval during dawn and dusk. The amount of natural lighting changes significantly during these times. This leads to over or under-exposed videos captured during these times as the aperture is open or closed too much, respectively, by the time the train arrives. This suggests that the frequency of adjustment needs to be increased to adjust the aperture based on the amount of natural light as close to the arrival of the train as possible. Since videos acquired in dawn and dusk were not properly exposed, we ran this method only for a day.

4.4.2 Variation II: Adjustment Frequency of 15 Minutes

In order to accommodate the significant change in lighting conditions during dawn and dusk, we adjust the camera every 15 minutes (at the hour, 15, 30, and 45 minutes past the hour). This is again done by comparing the minutes of the time on the computer clock to :00, :15, :30, and :45. In addition, the adjustment occurs only if the seconds are less than :06 so that the adjustment would only occur once, instead of several times during the entire minute, as in Variation I. We also restrict the adjustment to take place between 6 AM and 9 PM, to match the times of dawn and dusk, so that the camera is not being unnecessarily adjusted during the night.

From the videos acquired in this variation, we see that there is no fading in the

day time videos, and the videos acquired in dawn and dusk are not over or under-exposed. However, one problem we notice is that if a train is passing such that an adjustment time is missed, then the next adjustment occurs only after 30 minutes (from the previous adjustment). If there is another train that is coming by during this time also, then the difference in time between consecutive adjustments is 45 minutes, and so on. During this period of time, there could be changes in the background and lighting conditions that would cause the exposure to be incorrect in the video. This would then lead to incorrect background removal when processed with TMS. Hence, we improve upon this variation to account for the times when an adjustment is missed due to a passing train, in the next variation.

4.4.3 Variation III: Adjustment Frequency of 15 Minutes with Post-Train Adjustment

The camera is adjusted every 15 minutes just like in Variation II. However, we set a flag variable before recording a train, indicating that the camera needs to be adjusted after the train has passed. Then, after the train has passed, the camera is adjusted again. This would provide realtime adjustment of the exposure, just prior to the arrival of the train, for the next train video, in case the train happens to mask the 15 minute adjustment time. However, if the train did not pass by masking one of the fifteen minute adjustment times, still the adjustment after the train would take place.

The videos acquired with this variation also do not have any occurrence of fading. The night time videos, however, are completely black. This can be attributed to the fact that the lighting at the site for the night has not yet been properly designed, and that the lights do not turn on until a train has been detected. In this variation, we have found a solution to avoid fading. We now search for a solution to dampen the fluctuation in target intensity.

4.5 Approach to Dampening the Fluctuation in Target Intensity

Now that the fading problem has been solved, we attempt to dampen the fluctuation of the target intensity, without disrupting the solution to the fading. The following sub-sections will discuss the approach.

4.5.1 Plotting of Iris and Exposure Values

The first step in finding the cause of the fluctuation is to plot the values of the camera parameters during the 5 seconds of adjustment. This gives us an idea of how the adjustment takes place, and might give us some insight about the observed target intensity fluctuation.

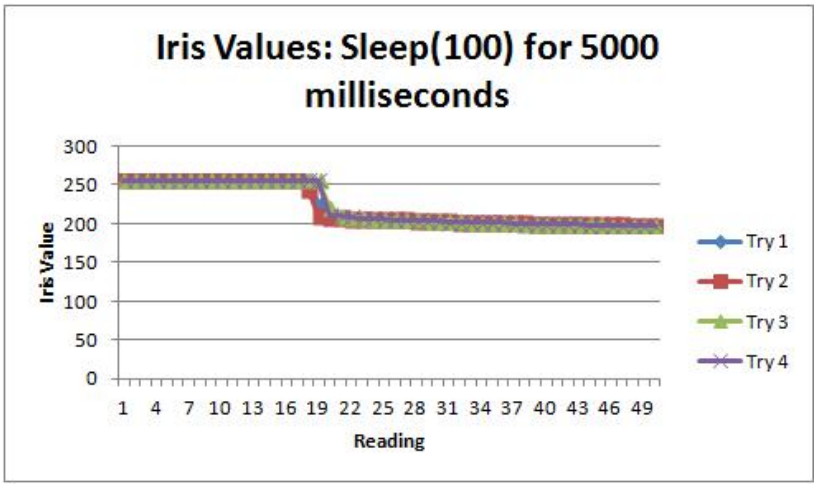


Figure 4.1: Iris values sampled every 100 milliseconds for a total of 5 seconds

We sample the iris values and record them every 100 milliseconds for a total of 5 seconds, as shown in Figure 4.1. Then, the same process is repeated for a total of 10 seconds, as shown in Figure 4.2. From Figure 4.2, we hypothesize that the parameters might have a periodic behavior after a certain time, as the values are rising back towards 200 again (starting from reading 73). We believe that the Nyquist sampling criterion may have been violated in the sampling performed thus far. Hence, we do

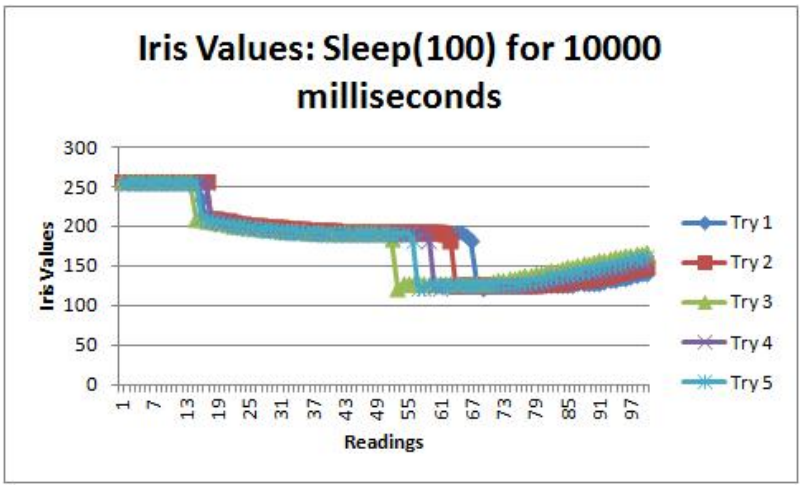


Figure 4.2: Iris values sampled every 100 milliseconds for a total of 10 seconds

not see the suspected periodic behavior.

The iris values are sampled and recorded every 10 milliseconds for a total of 5 seconds. We repeat this process three times, as shown in Figure 4.3. This figure confirms the hypothesis that the iris values are behaving periodically. Since the iris values behave periodically, we believe that the exposure property might also have a periodic behavior. Hence, we repeat the same process with the exposure values. The graphs shown in Figure 4.4 show that the exposure property also behaves periodically.

We now know for a fact that the iris and exposure properties behave periodically. With this fact in mind, we set out to find a solution to reduce the observed target intensity fluctuation between consecutive train videos.

4.5.2 Dampening the Target Intensity Fluctuation

Based on the fact that the iris and exposure values fall into periodicity after the first 1000 milliseconds, a new idea is used to adjust the camera. As mentioned before, the current adjustment system sets the exposure and iris properties of the camera on auto mode for 5 seconds. After these 5 seconds, auto mode is turned off on both these properties. As a result, the instantaneous value of both these properties is set when

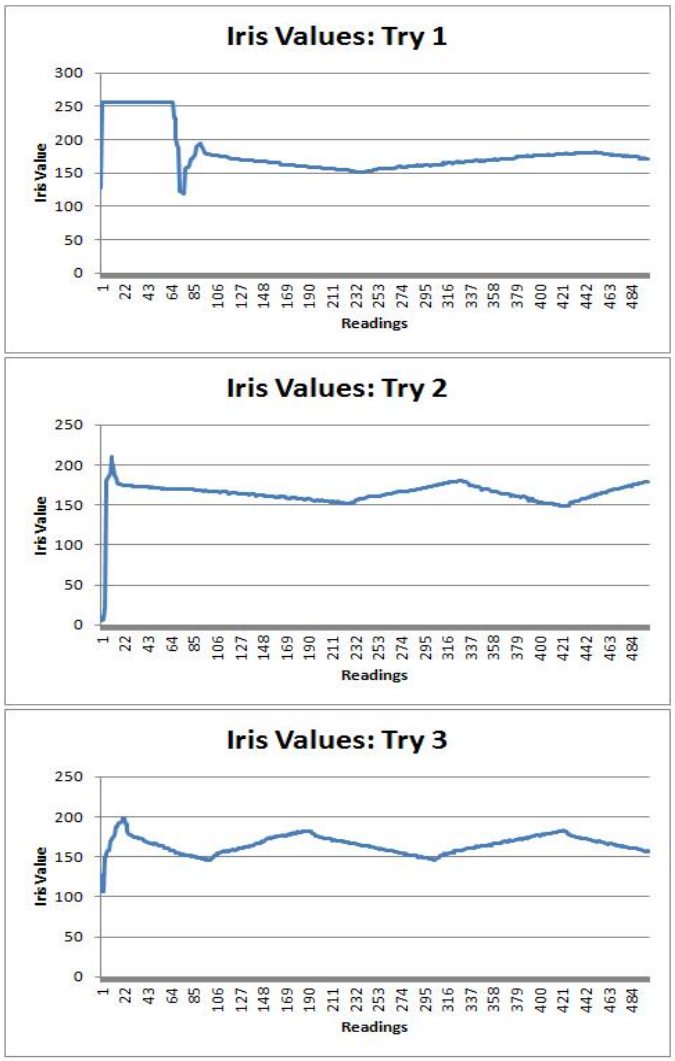


Figure 4.3: Iris values sampled every 10 milliseconds for a total of 5 seconds

auto mode is disabled. This value is suspected to lead to a brighter or darker image than desired, and could be the reason for the observed fluctuation in target intensity. Hence, the new technique we propose to dampen the observed fluctuation is to use the average of the periodic response of the exposure and iris properties during this time.

A fourth variation of the custom automation is implemented, using the averaging technique. This variation improves upon variation 3 that is described above. When we adjust the camera every 15 minutes (and after a train has passed), the value that is set for the exposure and iris properties are the average of their respective period-

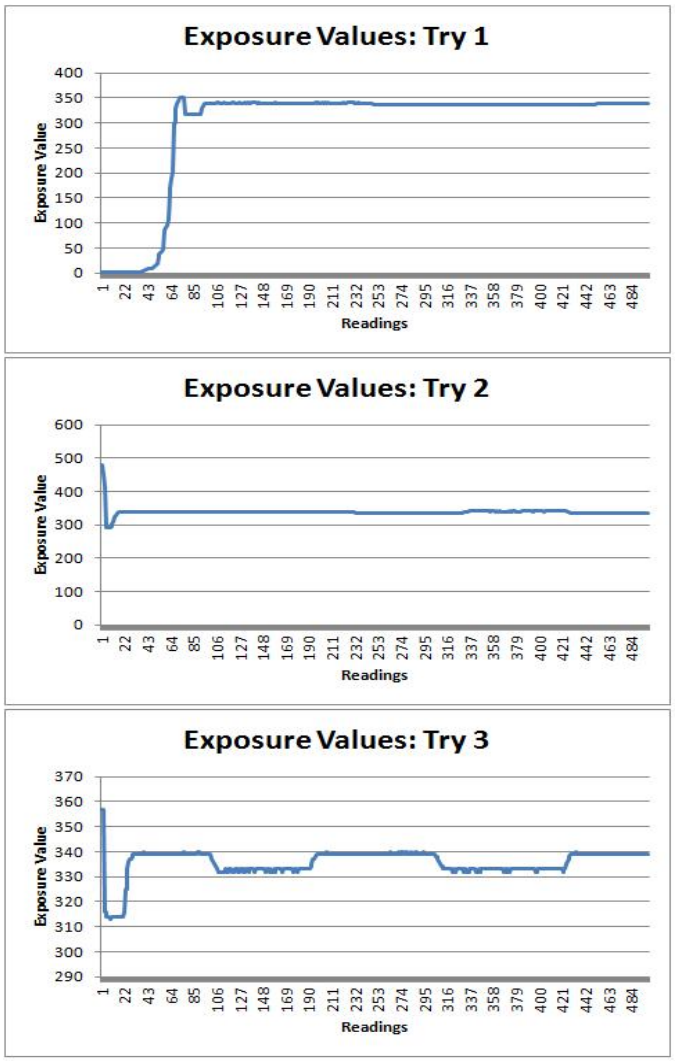


Figure 4.4: Exposure values sampled every 10 milliseconds for a total of 5 seconds

icities. We gather from the graphs in Figures 4.3 and 4.4 that the two properties fall into periodicity after approximately first 1000 milliseconds. So, when the averaging is implemented, the system waits for 1350 milliseconds to make sure that the periodicity has started. After that, we sample the values every 10 milliseconds for 3650 milliseconds, and the respective averaged values are set as the values for the two properties. This way, the total adjustment time is still 5 seconds, and thus trains will not be missed. Since the adjustment takes place every 15 minutes, the solution to the fading will not be affected. The set of videos that are acquired using this new variation do not show any fading. We will only be able to calculate the average intensities of a

black and white square from the ROI after we have collected a series of videos. The trend of these average intensities will tell us if this averaging technique has helped in dampening the fluctuation, as we hypothesize.

4.6 Video Pre-Processing with Histogram Equalization in TMS

Apart from the problems of fading and the target intensity fluctuation, a common problem seen in the intermediate TMS results is background over-subtraction in containers due to confusion between background and foreground. This occurs when the container is very similar in color to the sky (e.g. blue container against a blue sky). In cases of problems similar to this, a common image enhancement technique called histogram equalization is used.

The following procedure is used to perform histogram equalization in an image.

1. The histogram of the pixel values in the original image is formed.

2. The probability density function (PDF) is computed by dividing the count in each bin of the histogram by the total number of pixels.

3. From the PDF, the cumulative distribution function (CDF) is computed by simply maintaining a running sum at each bin of the histogram.

4. The new value for each pixel in the original image is calculated by multiplying the CDF of the old pixel value by 255.

Histogram equalization is known to improve the contrast of an image, when pixel values are very similar. An example is shown in Figure 4.5, where more details can be seen in the enhanced version of the image, post-histogram equalization. So, we write histogram equalization and include in TMS. By doing this, we hypothesize that the contrast of each frame will improve, and thus this will help TMS's background

Figure 4.5: (a) Original image, (b) Image after histogram equalization [10]

removal algorithm better distinguish between the background and foreground. In return, the background over-subtraction due to confusion between background and foreground will be fixed completely or at least occur less frequently.

In order to confirm our hypothesis, before running this new TMS on the new set of videos (from the four variations), we first run the new TMS on the same initial set of videos that was used to analyze the existing TMS problems in Chapter 3. The following sub-sections describe the results.

4.6.1 New TMS Results for the Initial Set of Videos

As mentioned above, the initial set of train videos is processed with the new version of TMS, and we tabulate the results, like we did before. Please refer to the table in Appendix E. From analyzing the table, we conclude that there is an overall improvement in TMS's performance. The segmentation is better when compared to the old TMS results for the same trains. There is no background over-subtraction in containers in the new results that had over-subtraction in the old results. Compared to the old TMS results, there are more trains that have perfect results when processed with the new TMS, which includes histogram equalization. A total of 89 videos are processed using the old TMS, out of which only 6 train videos had perfect

results. There were 34 videos that had very bad results, with incorrect segmentation, mosaicking, and/or motion blur problems. The remaining 54 videos had fairly good results, with segmentation errors in only a few containers.

A total of 88 videos are processed with the new version of TMS, out of which 28 videos have perfect results, and 23 videos have bad results with several segmentation errors. The rest of the videos have fairly good results with segmentation errors occurring in only few containers. Most of the videos with bad results were captured when the exposure and iris properties of the camera were set on auto mode. Hence, the video darkens when a bright container passes and brightens when a dark container passes. This fluctuation could have led to bad TMS results, as TMS compares consecutive frames for its calculations.

However, some of the daytime videos that had bad results for unidentified reasons in the old TMS results, have either perfect or fairly good results with the new version of TMS. It is also observed that all the videos that had fairly good or perfect results either have the same or better results with the new version of TMS. In addition, as hypothesized, background over-subtraction due to confusion between background and foreground is not seen in the new results. Therefore, this method is considered very successful in improving TMS results.

A few sample images of results from both versions of TMS are shown in Figures 4.6, 4.7, and 4.8. The images on the top are TMS results from the older version of TMS. The images on the bottom are results from the newer version of TMS. In Figure 4.6, we see that the background removal between containers was not perfect in the original results. This inaccurate segmentation leads to incorrect gap length calculations. However, when histogram equalization is included in TMS, the segmentation is perfect for the same train.

Similarly, in Figure 4.7, the segmentation is not correct on top of the containers. This makes TMS classify the loads as double stacks, instead of single stacks. We see

Figure 4.6: Top: TMS results from the old version of TMS. Bottom: TMS results for the same train from the new version of TMS.

that the new results have perfect segmentation at the top of the containers. Finally, in Figure 4.8, there is some background over-subtraction in two white containers in the original TMS results. This will make TMS detect each of those pieces of the same container as separate containers, again leading to incorrect gap length information. With histogram equalization, background removal is correct, which improves the performance of subsequent tasks in TMS. Since there is significant improvement in TMS's performance, we decide to process the new set of videos (from the 4 variations described above) also with this new version of TMS.

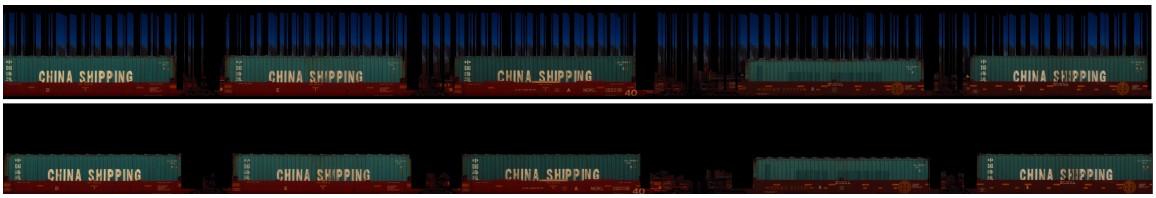


Figure 4.7: Top: TMS results from the old version of TMS. Bottom: TMS results for the same train from the new version of TMS.

Figure 4.8: Top: TMS results from the old version of TMS. Bottom: TMS results for the same train from the new version of TMS.

4.6.2 Target Intensity Results after Histogram Equalization

Although the averaging of the exposure and iris property values in variation 4 should dampen the observed fluctuation in target intensity, we wish to see what effect histogram equalization will have on the target intensity. Hypothetically, histogram equalization should also help in dampening the fluctuation because the histogram of the original image is being rearranged in such a way that the bins of the histogram are not clustered in one particular range of intensities. Keeping this in mind, MATLAB's in-built histogram equalization function is first run on the single frame images that were used to make the graphs in Chapter 3. Then, the average intensities of a black and white square from the ROI are calculated, the same way they were before. We calculate the average intensities only on the set of frames for the exposure settings were adjusted using the new ROI described in the previous chapter.

The old and new average intensities of both the white and black squares are plotted, as shown in Figures 4.9 and 4.10. From these graphs, we see that the fluctuation of the average intensity of the white squares has dampened. There are several places in the graph where the change in the average intensity of the white square is more gradual than before. The fluctuation has also dampened for the black squares. However, there is a major spike in Figure 4.9 from train 20 to 21 and from train 22 to 23. The reason for this is that train 21 and 22 were trains that had passed by in the night. Hence, the frame was black except for the checkerboard target. When histogram equalization is performed on these frames, most of the frame becomes white, including the black squares, as shown in Figure 4.11. This results in an inaccurate average intensity for the black square for these frames.

Since the fluctuation in the average target intensity has dampened after histogram equalization (Figure 4.10), this will also further dampen the fluctuation from video to video when the new videos are processed with the new version of TMS. We now proceed to process the new set of videos (from the 4 variations) with the new version

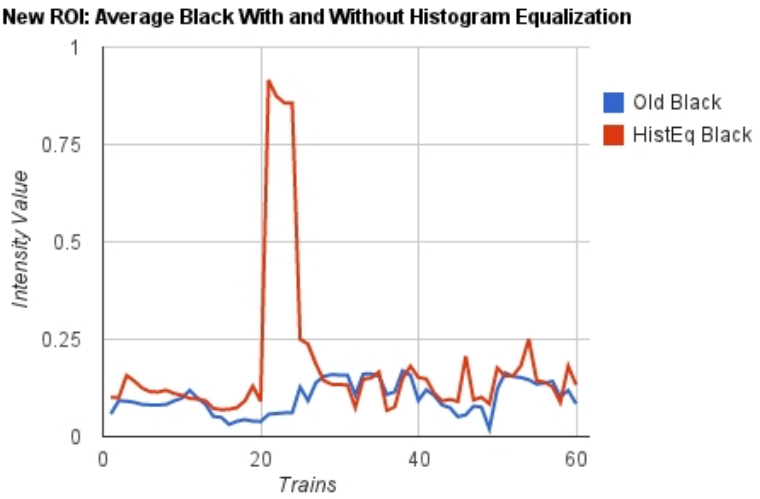


Figure 4.9: Comparison of average intensity of black square in ROI with and without histogram equalization

of TMS. These results are discussed in the next chapter.

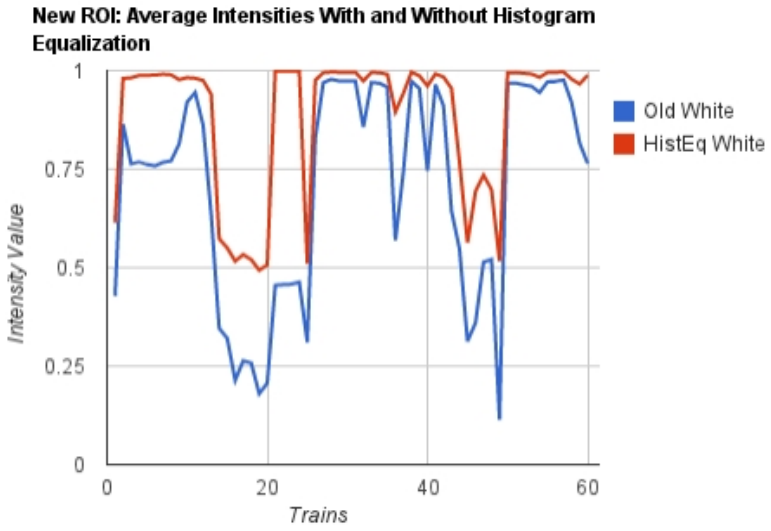
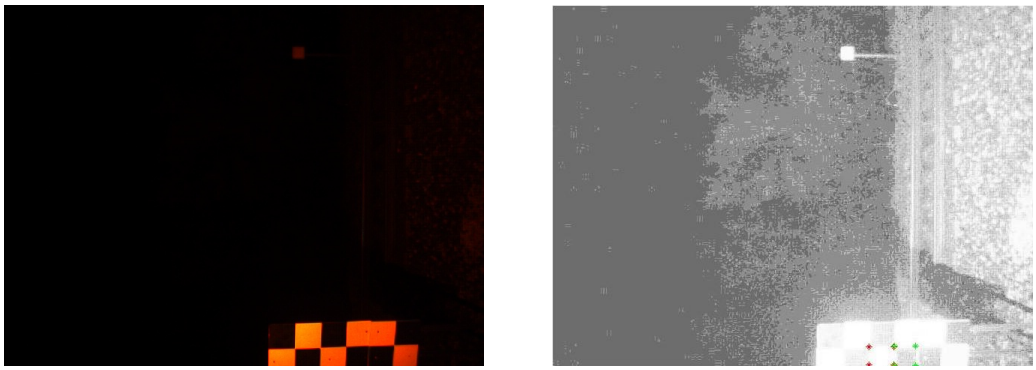


Figure 4.10: Comparison of average intensity of white square in ROI with and without histogram equalization



(a) Original Image (b) Histogram Equalized Image

Figure 4.11: Histogram equalization performed on nighttime frames produces inaccurate average target intensity values.

CHAPTER 5

ANALYSIS OF INTERMEDIATE TMS RESULTS FOR THE NEW VIDEO SET

The new set of videos acquired from the four variations described in Chapter 4 is processed using TMS with histogram equalization. A table is maintained to record TMS results for train videos from each of these variations. These tables can be found in Appendix F. We discuss the results for the videos from each of those variations in the following sections.

5.1 Variation I: Adjustment Frequency of 30 Minutes

In this variation, we adjusted the camera every thirty minutes (at the hour and half-past the hour). This variation was tested only for a day as there were many problems with this version (as described in Chapter 4). As a result, only 9 videos were captured in this time period. There is only 1 train with perfect results, and 3 trains have significant segmentation errors. The rest of the videos have moderate results with minor segmentation errors. Figures 5.1 to 5.4 show results from the trains under this variation.

Figure 5.1 shows one of the problems that is observed with TMS results. As seen, there is major background over-subtraction in the red container. This sort of segmentation error leads to incorrect classification of the loads. Figure 5.2 shows another problem that is seen in this variation. We see background under-subtraction between containers. This leads to incorrect gap-length calculations between consecutive containers.

Figure 5.1: Variation 1 - Background over-subtraction seen in red container

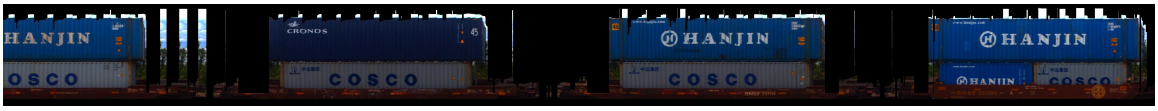


Figure 5.2: Variation 1 - Background under-subtraction in between containers

On the other hand, Figures 5.3 and 5.4 show TMS results from the one train that had perfect results. We see that the blue containers and the white containers are perfectly segmented. This is the sort of results that we are aiming for as this will give us correct gap length information as well as correct classification of loads as single stacks, double stacks or trailers.

Figure 5.3: Variation 1 - Perfect segmentation around blue containers

5.2 Variation II: Adjustment Frequency of 15 Minutes

In this variation, we adjusted the camera every 15 minutes (at the hour, 15, 30, and 45 minutes past the hour). We captured 18 videos when this variation was run. One video was over-exposed and so failed TMS. Another video has major segmentation problems. Six videos have perfect TMS results, and the remaining videos have fairly good results with minor segmentation problems. Segmentation errors due to confusion between background and foreground are not seen. Figures 5.5 to 5.8 show TMS results for trains that were captured as this variation was tested.

Figures 5.5 and 5.6 show perfect results from trains in this variation. We see that the blue containers are perfectly segmented even though the sky is very close in color

Figure 5.4: Variation 1 - Perfect segmentation

to the container. One point to note is that we see that a little bit of the sky has not been removed at the top of the containers in both the figures. However, this is not a major problem as we only care that the segmentation at the vertical edges are perfect, as these edges are used to calculate gap lengths. This amount of sky being seen at the top of the container in no way affects these calculations, and the loads will be classified as a double stack.

Figure 5.5: Variation 2 - Perfect segmentation

Figure 5.6: Variation 2 - Perfect segmentation around blue containers

Figures 5.7 and 5.8 show some of the problematic TMS results. In Figure 5.7, we see major background over subtraction in the white containers. In Figure 5.8, we see that most of the containers have been subtracted due to the video being over-exposed. Since some containers are completely subtracted, the gap-length information between containers would be inaccurate. Since incorrect gap-length information is fed into TSS, the train will be given an incorrect aerodynamic score.

Figure 5.7: Variation 2 - Significant background over-subtraction

Figure 5.8: Variation 2 - Background over-subtraction due to the video being over-exposed

5.3 Variation III: Adjustment Frequency of 15 Minutes with Post-Train Adjustment

In this variation, not only did we adjust the camera every 15 minutes (at the hour, 15, 30, and 45 minutes past the hour), but we also adjusted the camera after a train passed by. By having post-train adjustment, we make sure that the camera has been adjusted if a train passed by masking the 15 minute adjustment time. When this variation was tested, 34 videos were captured. Twelve videos have perfect TMS results, and 5 videos have major segmentation problems. The rest of the videos have minor segmentation errors. Again, segmentation errors due to confusion between background and foreground are not seen. Figures 5.9 to 5.12 show TMS results for this variation.

Figures 5.9 to 5.11 show some of the problems that are observed in TMS results. Parts of the containers are subtracted in Figures 5.9 and 5.10. In both cases, a whole vertical strip is subtracted in the loads. This will lead to wrong edge detection and gap-length calculations. A relatively small value will be calculated as the gap-length, when actually it is the width of the vertical strip that has been completely subtracted from the container. In Figure 5.11, there is background under-subtraction between containers. In this case, two containers together would be detected as one. As a result, some gap-lengths between these containers would not be calculated at all (missing gap-lengths). Figure 5.12 shows a sample of the perfect segmentation that are seen

in the trains that have perfect results.

Figure 5.9: Variation 3 - Background over-subtraction

Figure 5.10: Variation 3 - Significant background over-subtraction

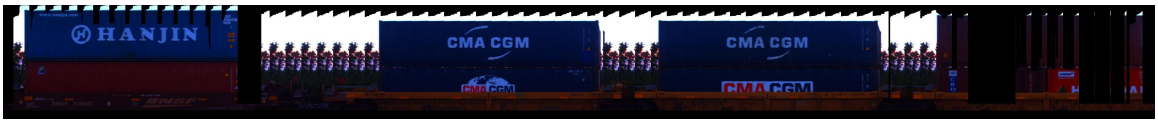


Figure 5.11: Variation 3 - Background under-subtraction between containers

5.4 Variation IV: Adjustment Frequency of 15 Minutes with Post-Train Adjustment and Parameter Averaging Technique

This variation not only implemented a technique to avoid fading, but it also averaged the parameter values to work around target intensity fluctuation. Hence, we discuss the TMS results and the target intensity results in two different sub-sections.

5.4.1 TMS Results

We acquired 77 videos when this variation was run. Out of these, 30 trains have perfect TMS results. Five videos have major background over-subtraction in containers. Most of these trains passed either at dawn or dusk. Hence, due to insufficient lighting, the videos were darker than preferred. This should be solved when proper lighting has been installed at the site. The rest of the videos have minor background removal

Figure 5.12: Variation 3 - Perfect segmentation

problems in one or two containers. Again, segmentation errors due to background-foreground confusion is not seen in these results. Figures 5.13 to 5.16 show some results for this variation.

Background over-subtraction is seen in Figure 5.13, while minor background under-subtraction between containers is seen in Figure 5.14. As already mentioned before, under-subtraction will lead to incorrect gap-length data. Figures 5.15 and 5.16 show a sample of some perfect TMS results from some of these trains. We especially see that the two blue containers in Figure 5.16 are perfectly segmented even though the sky is very close in color to the containers. Again, we are not concerned with the little bit of sky seen at the top of the containers because the loads will be classified as a double or single stack anyway based on height.

Figure 5.13: Variation 4 - Background over-subtraction

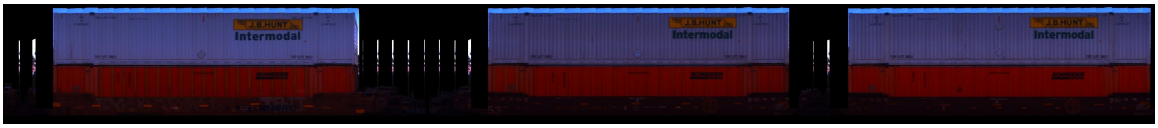


Figure 5.14: Variation 4 - Major background over-subtraction

5.4.2 Target Intensity Results

The average intensity of a white and black square from the ROI on the checkerboard target is calculated, similar to the methods described in Chapter 3. The two graphs are shown in Figures 5.17 and 5.18. The particular trains marked with an 'O' on

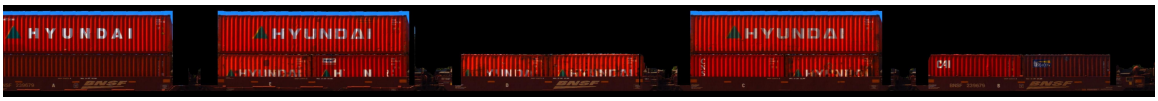


Figure 5.15: Variation 4 - Background under-subtraction between containers

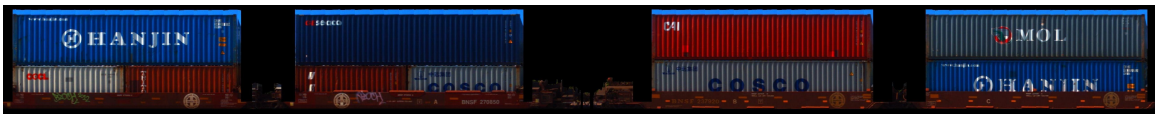


Figure 5.16: Variation 4 - Perfect segmentation

these graphs correspond to the five trains that had major segmentation errors. As mentioned before, most of these trains had passed at times when there was insufficient natural lighting.

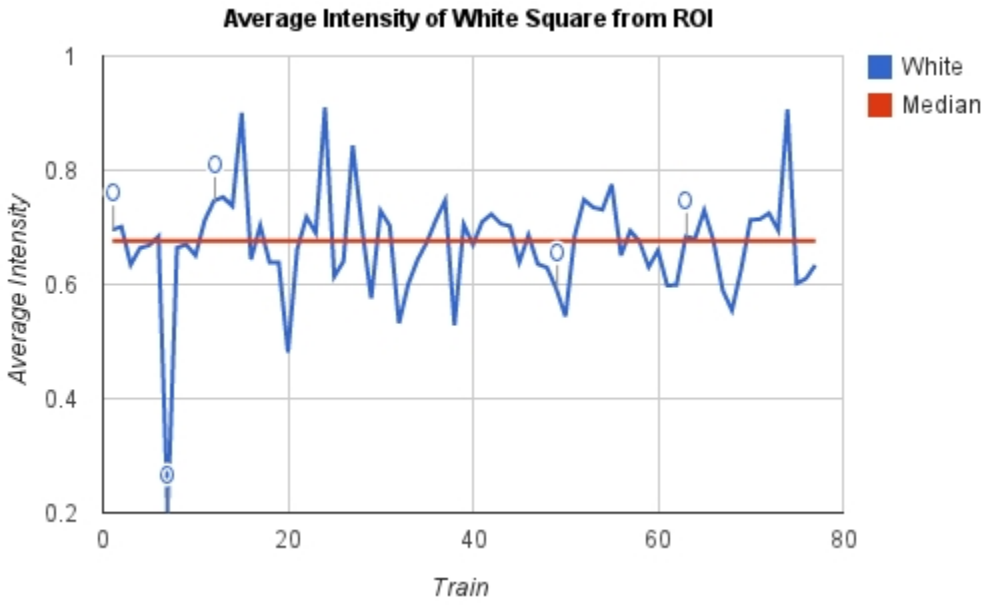


Figure 5.17: Average intensity of white square from ROI

As seen from Figure 5.17, the maximum average value of the white square is about 0.9. The minimum value, if we exclude the obvious outlier, is about 0.5. The median of the white values is approximately 0.7, which is about half-way through the range of values, 0.4. By averaging the exposure and iris properties of the camera, the average intensity of the white square has been restricted to a range of values between 0.5 and 0.9. As seen from the graphs in Figures 3.10 and 3.11, any average intensity values

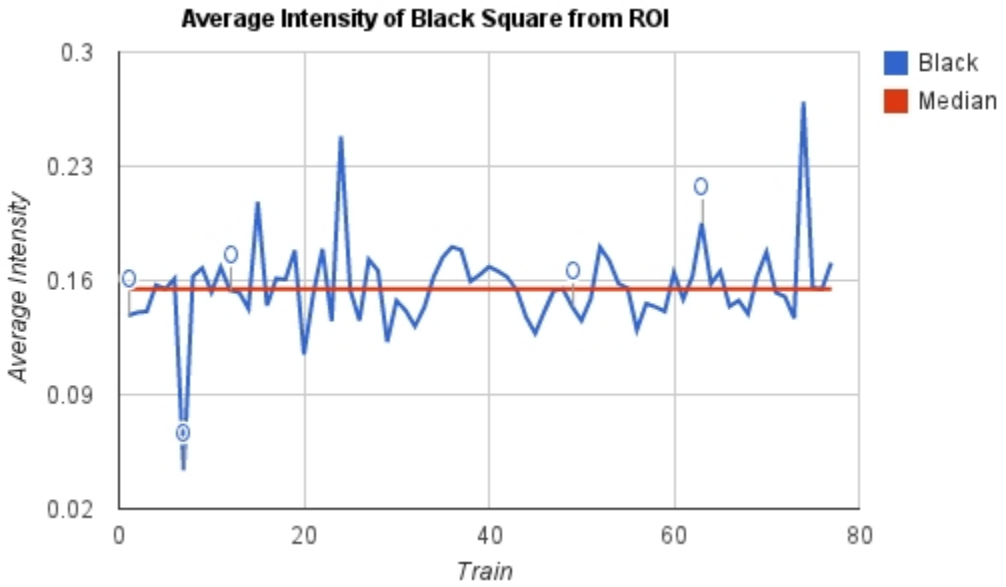


Figure 5.18: Average intensity of black square from ROI

greater than 0.9 produced problematic TMS results.

As seen from Figure 5.18, the maximum average value of the black square is about 0.25. The minimum value, if we exclude the data point corresponding to the outlier in Figure 5.17, is about 0.1. The median of the white values is approximately 0.2, which is very close to half-way through the range of values, 0.15. By averaging the exposure and iris properties of the camera, the average intensity of the black square has been restricted to a range of values between 0.25 and 0.1. Most of the trains used for initial analysis in Chapter 3 had problematic results, and their corresponding black average intensity values were between 0.1 and 0.25, as their corresponding white averages were greater than 0.9. However, we see that after averaging the camera properties, even though the average values of the black square are still in the same range, there were not many trains with problematic results as their corresponding white average values were contained to below 0.9.

5.5 Explanation of Successful Results

The non-realtime adjustment method of acquiring videos has helped in avoiding fading, which was caused by the camera not physically adjusting to the values set for its parameters through the software. In addition, TMS results from the new sets of videos show an improvement in TMS performance. As seen from Figures 5.17 and 5.18, the average target intensity fluctuation is not as substantial as those seen in Chapter 4. Indeed, averaging the exposure and iris properties of the camera have helped in containing the values within a range, and flatten the fluctuation. Even if there was some fluctuation, as we noticed in Chapter 4, histogram equalization included in TMS also would have further flattened any fluctuation. This should have also helped in making all day time videos come to be in the same scale when run through TMS.

So far, we have worked to solve a key problem involving train videos captured during the day time, under generally good and perhaps variable natural illumination conditions. However, videos captured either in dawn or dusk cause problems with TMS due to insufficient ambient lighting. In addition, trains that pass by during the night are not captured due to the lighting system still being under development. We also anticipate that videos captured on over-cast days (during winter) might also have difficulties with TMS.

Currently, we are not capturing trains at dawn, dusk and night. Hence, we are not able to provide BNSF with results for all trains that pass by the MV site at Sibley, MO. However, to reduce the fuel consumption costs of BNSF, it is necessary to properly capture and score all trains that pass by, regardless of ambient lighting conditions. This can be achieved with a lighting system at the site, so that videos captured on overcast days or during the night can also be properly analyzed. In the next chapter, we present the groundwork we have done on the designs for a lighting sub-system for the MV system at Sibley, MO. This will enable the MV system to

operate 24/7 and provide complete analysis of all IM trains that are traveling along the TRANSCON.

CHAPTER 6

DESIGN CONSIDERATIONS FOR THE LIGHTING SUB-SYSTEM

Lighting for the site is important, as mentioned in Chapter 5, because the trains that pass by either during dawn and dusk have problematic TMS results. In addition, video capturing has been disabled currently for trains passing during night. TMS's requirements have been discussed in detail in previous chapters. Further, the project's sponsor, BNSF, has also specified that the lighting sub-system must be as cost effective as possible and that the lights be mounted in such a way so that they do not blind the train's engineers. Apart from this, we need the lights to instantly turn on to full brightness so that there is no variation in illumination over the frames of the videos. This is essential for TMS to perform well, as it correlates two consecutive frames (refer to Chapter 2). Keeping all these requirements in mind, we design a lighting sub-system for the MV system at Sibley, MO. Lighting design has two main components: the choice of lights and their mounting orientation. We have some lighting installed at the site currently; however, they do not provide enough lighting for the scene because they keep burning out frequently. As a result, we are in need of selecting and installing a lighting system which will help capture videos that pass TMS successfully. This chapter describes the considerations and the groundwork we have done for the lighting design for nighttime and low-light conditions (i.e. overcast days). Based on the initial conclusions on lighting described in this chapter, lighting design will have to be further explored and properly implemented in the future.

6.1 Current Lighting at the Site

Six halogen lights, mounted vertically on the communication tower, are currently installed as part of the MV system. They are turned on after sunset every time an incoming train triggers the MV system. These lights, however, do not provide adequate lighting for the trains that pass by during night. The problem with these halogen lights is that the bulbs blow out frequently, either due to weather conditions or the frequent cycling on and off. As a result, someone has to make a trip to the site to replace the blown out bulbs. Hence, videos of trains passing by during the night time are not captured. Based on the problems with the current lighting system at the site, we set out to explore other configurations and types of lighting available.

6.2 Exploration of LED Lights

We consider the following two points:

1. We are concerned that bugs are attracted to the halogen lights, and could appear in the video recordings at night. We first find the cause of this attraction: Are bugs attracted to halogen lights because of the warmth or because those lights emit a certain wavelength of light that attracts bugs? If either of these reasons is true, then can this attraction be reduced by utilizing LEDs? We find that bugs are equally attracted to halogen and LED lights due to the heat produced and certain wavelengths of light emitted by the lights. Hence, this problem would exist irrespective of the type of light used [11]. The need for this investigation will become clear when we discuss the light's mounting orientation later.

2. We compare the cost and lifetime of the two types of lights. Halogen lights are cheaper but generate a lot of heat. In addition, halogen lights blow out frequently. Since bulb replacement typically can take days, data collection is

disrupted and TMS performs poorly on the videos acquired during this period. On the other hand, LED lights have long life-times and produce significantly less heat, but are more expensive. However, since their efficiency is much higher, their operation costs are lower. Hence, significant energy savings can be achieved when using LED lights [12].

Even though we cannot avoid bugs by using LED lights, we still decide to purchase a sample LED light for testing purposes. We arrive at this decision considering that data collection would not be disrupted frequently due to blown out bulbs. In addition, by using LEDs, we will be saving energy and therefore environmentally friendly.

6.2.1 Purchase of a Sample LED Light

We purchase an LED light from Raytec Systems Inc., a company that sells outdoor LED lighting products. In order to select the correct product, the following details about the site are required. The camera is 30 feet from the railway track, and at a height of 20 feet. In addition, each frame is 480 by 640 pixels, and there are 25 pixels per foot. Hence, the camera's field of view is approximately 20 feet by 25 feet, and we need that to be lit sufficiently. Figure 6.1 shows the details described above in a plan view diagram. Given these specifications, Raytec suggested that their RL50-AI50 model of light would serve our purpose. The light consists of 50 LEDs and can be set-up in angles between 50 to 120 degrees. Figure 6.2 shows the photometric diagram, which shows the dispersement pattern of the light, for this model of light. Ideally, the train should be in the area indicated by the red arrow in Figure 6.2, where there will be even illumination. This will occur at a 60 degree setting.

When we purchased the light, we ordered the RL100-AI50 model [14]. This light consists of 100 LEDs and can be set up in angles between 50 and 120 degrees. We purchased this model just to make sure that we provide sufficient lighting for the scene. However, when we installed the light at the site, the light was still several

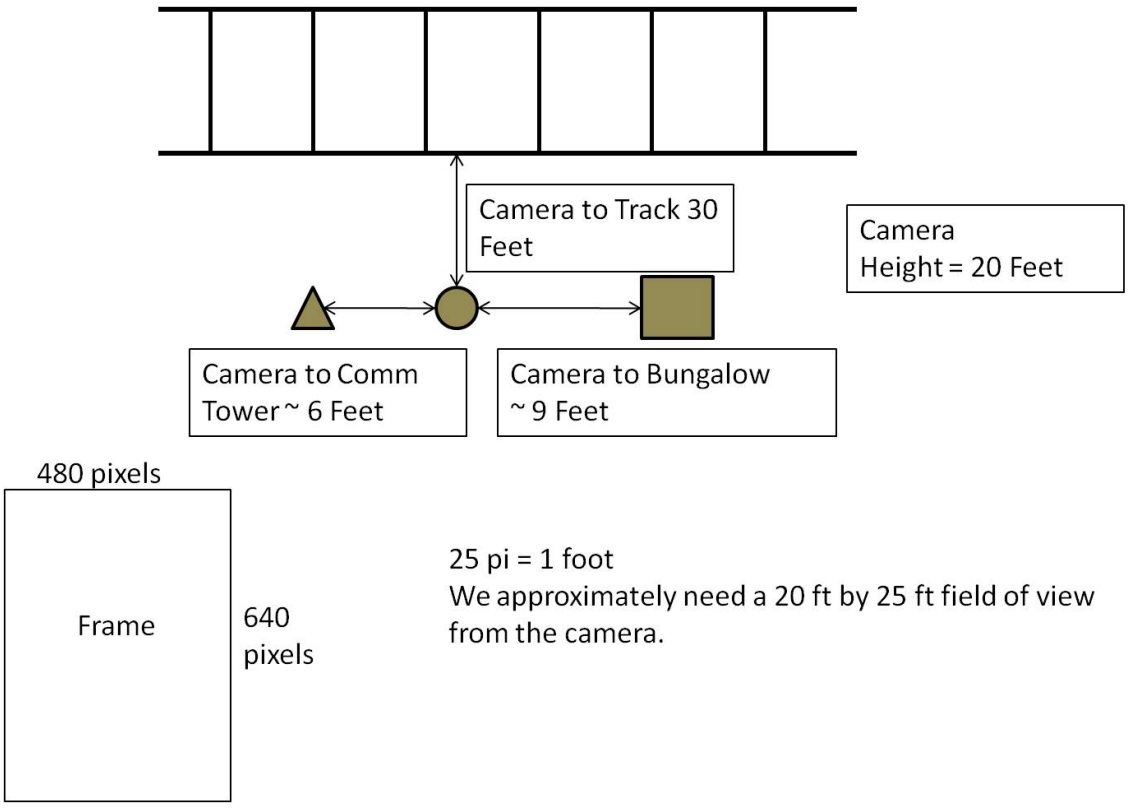

Camera to Track 30 Feet
Camera Height = 20 Feet
Camera to Comm Tower ~ 6 Feet
Camera to Bungalow ~ 9 Feet
480 pixels
Frame
640 pixels
25 pi = 1 foot
We approximately need a 20 ft by 25 ft field of view from the camera.

Figure 6.1: Measurements required to select lighting.

times duller than the required amount of lighting.

6.2.2 Photometry of Lights

We next compare how the intensity of light decreases with distance from both the LED and halogen lights. This will help us see which of the two types lights is brighter as we move farther away from the light source. In order to performed this experiment, we form a grid using the tiles on the floor in the lab. Each tile is 2 feet by 2 feet. We place each light at the origin of this grid, and use a Spectra Professional IV Digital Exposure meter [15] to measure the intensity of light every 2 feet away from the light directly, and 2 feet to the right and left of the light. We use a tripod to make sure that the height at which these measurements are taken is constant. A diagram of the setup is shown in Figure 6.3, where the black dots represent the places where light

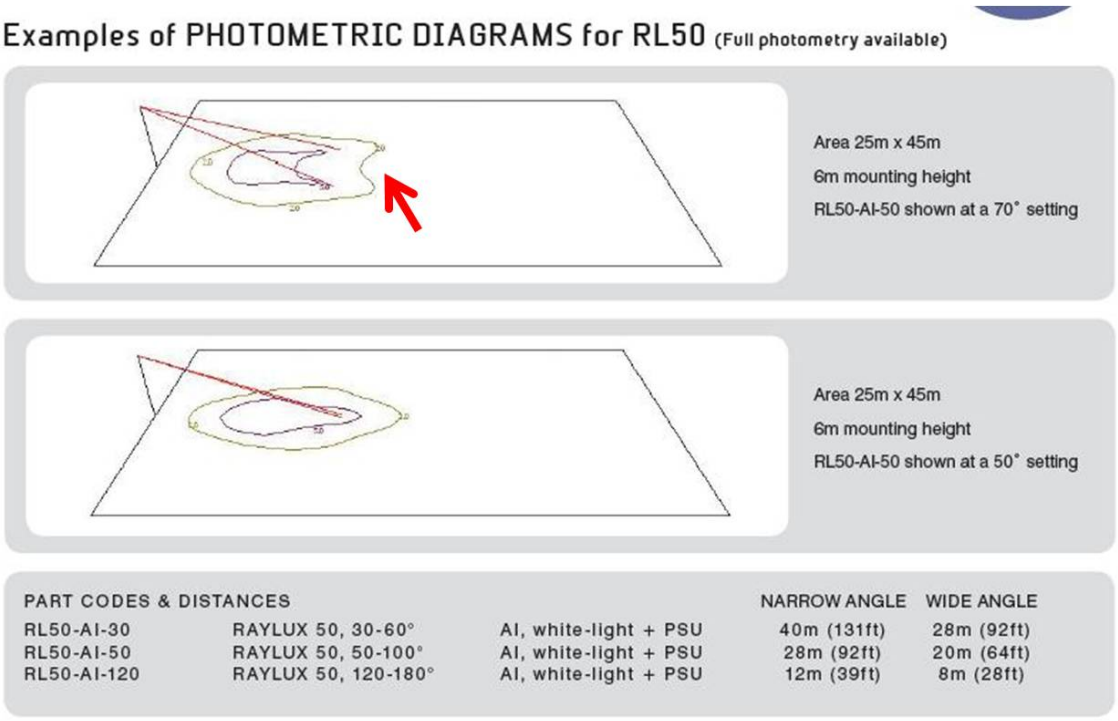

Examples of PHOTOMETRIC DIAGRAMS for RL50 (Full photometry available)
Area 25m x 45m
6m mounting height
RL50-AI-50 shown at a 70° setting
Area 25m x 45m
6m mounting height
RL50-AI-50 shown at a 50° setting
PART CODES & DISTANCES
NARROW ANGLE
WIDE ANGLE
RL50-AI-30 RAYLUX 50, 30-60° AI, white-light + PSU 40m (131ft) 28m (92ft)
RL50-AI-50 RAYLUX 50, 50-100° AI, white-light + PSU 28m (92ft) 20m (64ft)
RL50-AI-120 RAYLUX 50, 120-180° AI, white-light + PSU 12m (39ft) 8m (28ft)

Figure 6.2: Photometric diagram for RL50-AI50 [13]

intensity readings are obtained. Light readings could not be obtained at unmarked places as there are tables, equipment, etc. at those points. Table 6.1 shows the light meter readings at the corresponding numbered point in Figure 6.3. We hypothesize that the intensity of light should decrease as we move away from the light.

As expected, the intensities of both lights generally decrease as the distance from the light increases. We see some irregular readings for both lights at some points. Several readings were taken at these points to confirm the observed values. We suspect that the cause for these irregular readings could be due to reflected light from shiny surfaces, such as metals. In addition, when we inspected the lights, we found that the halogen light bulb itself has small piece of glass that pokes out. This spike-like part of the bulb could have had some effect in the irregular readings observed for the halogen light. However, from this experiment, we see that at a distance of 12 feet, the intensity of light from the LED light was greater than the halogen light. Since the LED light is brighter than the halogen light at 12 feet, we conclude that the LED

Table 6.1: Light meter readings at each numbered point in Figure 6.3. All readings in LUX.

-	RL50-AI50 (LED)	Halogen
1	297 lux	113 lux
2	110 lux	683 lux
3	253 lux	60 lux
4	915 lux	990 lux
5	413 lux	172 lux
6	571 lux	947 lux
7	904 lux	700 lux
8	199 lux	829 lux
9	689 lux	581 lux
10	82 lux	226 lux
11	117 lux	467 lux
12	524 lux	385 lux
13	139 lux	234 lux
14	786 lux	284 lux
15	476 lux	269 lux
16	151 lux	190 lux
17	560 lux	222 lux
18	379 lux	203 lux

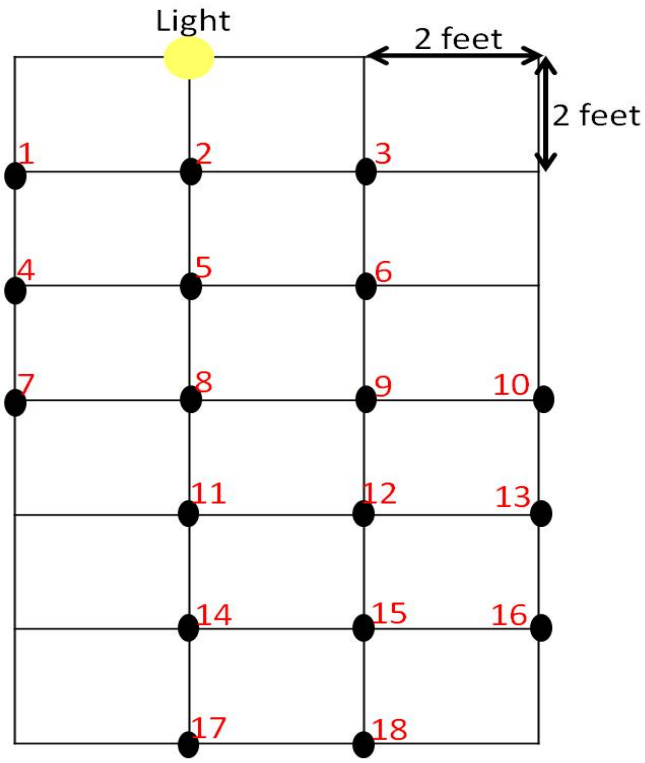


Figure 6.3: Grid Set-up to measure the dispersement of light

light will still be brighter than the incandescent lights at a distance of 30 feet.

6.2.3 Required Amount of Lighting

As we already mentioned above, the LED light was not sufficient for the site. Hence, we determine the amount of light required in order make the final decision between halogen and LED lights. This will also help us determine how many individual light units would have to be purchased, if we decide to install LEDs.

When some of my colleagues in the lab visited the site, they took several light intensity readings using a Spectra light meter on a vertical grid formed using a tape measure. These intensity readings were taken when three lights were functioning. The maximum intensity measured was 300 LUX. Since, the scene was well lit when all six lights were functioning, we can calculate our required amount of light to be 600 LUX. We then add another 100 - 150 LUX to this to add some cushion to make

sure we have enough lighting for the scene. Hence, we require about 700-750 LUX in order to sufficiently illuminate the field of view of the camera.

Based on this light intensity requirement, we want to calculate the number of units that will need to be purchased if we decide to install LEDs. So, the LED light is placed 30 feet from a wall (since the lights will be mounted 30 feet from the tracks at the site), and the intensity of light on a grid on the wall is measured. We measure the intensity of light at every point on the grid to be 150 LUX. Now, given that one unit of the RL100-AI50 model of light produces an intensity of 150 LUX at 30 feet and that we require 700 - 750 LUX for sufficient lighting at the site, we will need five of these RL100-AI50 units. One of these units cost between $700 to $750.

In addition, we consulted Raytec to ask if there were any other models of light that would work for our application. They said that we could try the fusion model of the same lights, RL100F-AI50 [16]. This should also work for our application; however, we need to purchase the lights and test it out to make sure that it works well for our application. In other words, they did not guarantee that one unit of the fusion light model would provide more illumination than one unit of the classic light model at a distance of 30 feet. Since there was no guarantee before purchasing the lights that they would work for us and these lights are expensive, we decided to explore other options of lighting.

We next explore lighting from Holophane, a company that sells lighting products for sign boards on highways, and other applications such as parking lots, etc. Unfortunately, the contact at Holophane with whom we consulted brought to our attention that none of Holophane's lights instantly turn on to full brightness. The lights may take up to 20 minutes to get to full brightness, depending on outside temperature. This violates our basic requirement of lighting that would help us capture videos that would pass TMS successfully.

However, if we turn on the lights as soon as we sense that the amount of natural

lighting is below a certain threshold value and turn it off when the amount of natural lighting is above this threshold, we will be able to utilize Holophane lights. With this in mind, we consult the Holophane representative with particulars of our site. The representative suggests that the Predator model of lights would best work for our application [17]. Figure 6.4 shows the photometry for the light as simulated by the representative. We also see that Holophane suggests that we purchase 4 units of the Predator model. One thing to take note of in Figure 6.4 is that the intensity values are in footcandles. One footcandle is about 10.76 LUX. Hence, these 4 units of lights together should provide us with an average illumination of approximately 710 LUX, which is within our range of required amount of light that we calculated above.

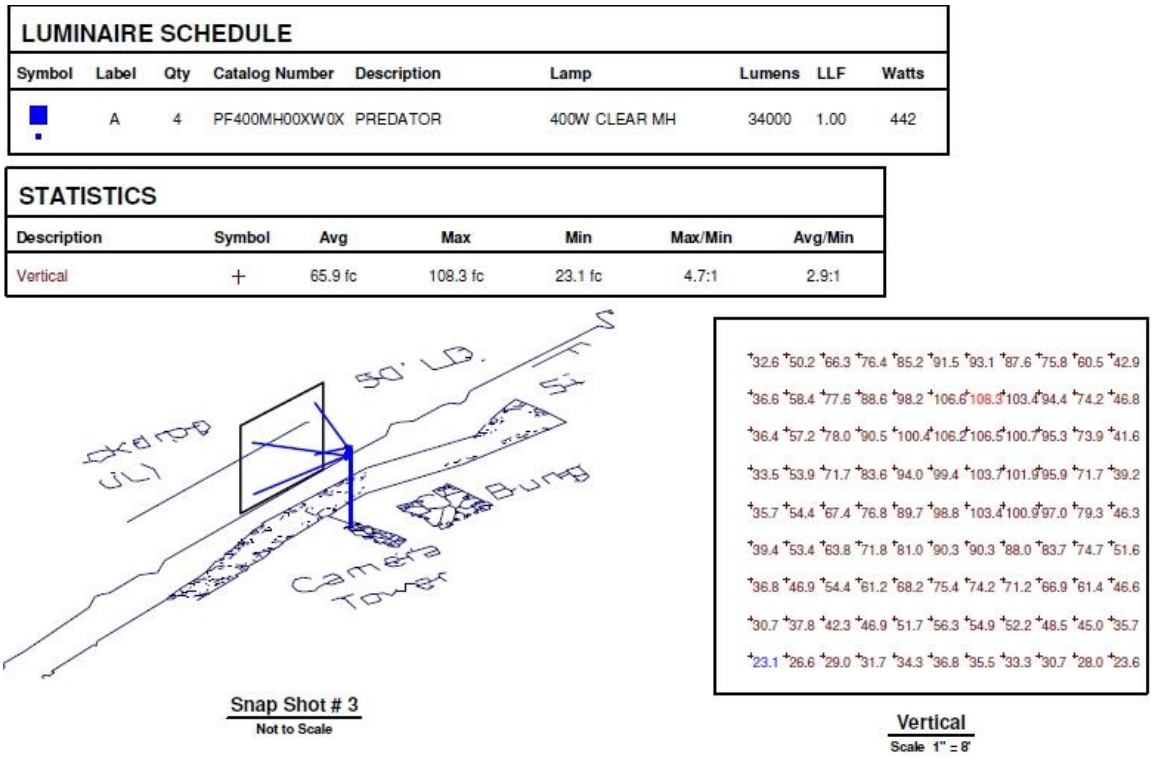


Figure 6.4: Lighting suggested by the Holophane representative

The lights need to be purchased along with mounting hardware. The mounting hardware is either a stainless steel yoke or a zinc plated yoke [18], of which the stainless steel yoke is costlier. When we inquired about the pricing information,

the Holophane representative calculated the cost of one unit of the Predator with a stainless steel yoke to be $825. The final price that we pay, if we decide to buy the Predator, would be no more than $825 per unit of light.

However, one thing that needs to be clarified with the Holophane representative is the mounting orientation of the lights on the camera tower. Should the four units of lights be mounted vertically, in one line, or on two horizontal bars mounted one on top of the other on the camera tower? We tried to contact, repeatedly without success, the Holophane representative to clarify the mounting orientation of the lights. However, we have conducted some simple lighting experiments in the laboratory that are described in the following section, which may provide some insight. So, we can use the lights suggested by Holophane if we leave the lights on during the entire night. Otherwise, we will either have to use halogen lights or probe further into Raytec's lights to meet our requirements.

6.3 Light Mounting Considerations

We now discuss the considerations and requirements for mounting locations and orientations for the lights. The lights can either be mounted on the camera tower, just below the camera, or on the communication tower which is approximately 5 feet away from the camera tower. Mounting the lights below the camera means that the lighting will be a straight cone, normal to the train. However, since the lights are just below the camera and since bugs are attracted to the light source, the videos acquired may have a lot of bugs showing up in the scene. TMS may not be able to analyze these videos well. If the lights are mounted on the communication tower, the light would be projected at an angle. This would illuminate the scene unevenly. However, since bugs are physically separated from the camera, capturing of clean ('bug-free') videos is possible. Figure 6.5 shows the dispersement of light for both the mounting options

described above. It can be seen in the image that the light on one side would have to travel further; therefore, the drop-off in light intensity would be more on that side. We have to decide which option would provide us with videos that successfully pass TMS.

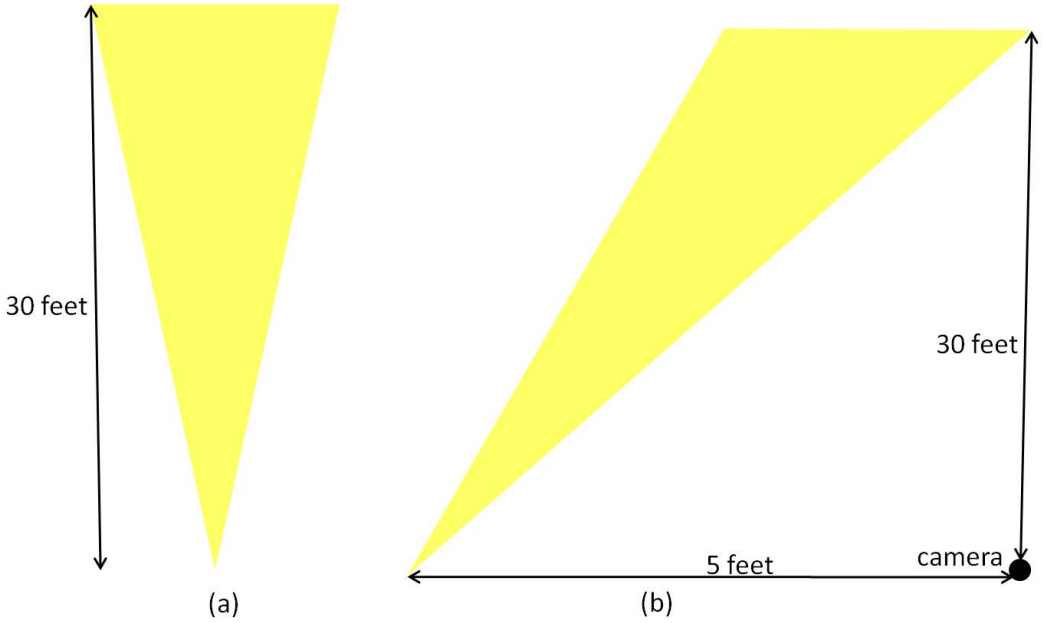


Figure 6.5: (a) A direct cone if lights were mounted under the camera, (b) a skewed cone if lights were mounted on the communication tower

6.3.1 Determining the Best Location for Mounting the Lights

We performed two experiments in the lab to determine the optimal mounting configuration.

Experiment 1: Determining the Location for Mounting the Lights

A grid is drawn on the wall, similar to the one shown in Figure 6.6, and an LED light is projected onto the wall directly. This simulates the light source being mounted on the camera tower, just below it. Light intensity readings (in LUX) are taken using a Spectra meter at each point of the grid, marked with a black dot. Then, the

light source is moved 34.5 inches to the left and angled at 35 degrees so that it still illuminates the grid's center on the wall. This simulates the lights being mounted on the communication tower. The readings are shown in Table 6.2. The values in bold face indicate the center of the grid.

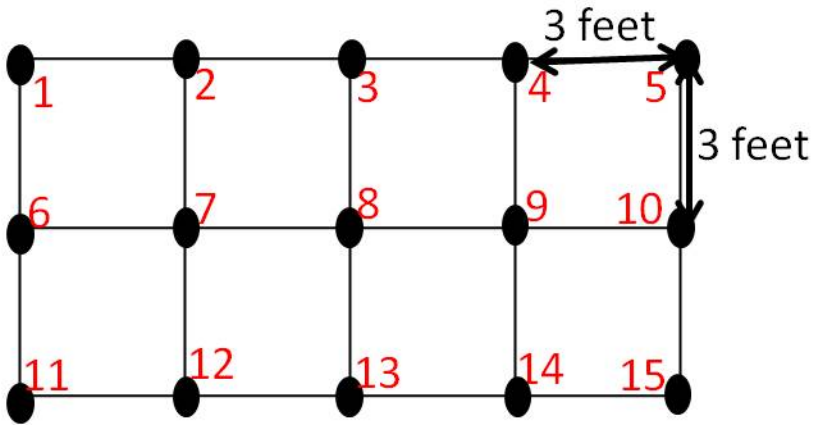


Figure 6.6: Grid formed on Wall to take light intensity readings

Table 6.2: Light meter readings at each numbered point in Figure 6.6. All readiings are in LUX.

-	1	2	3	4	5
Directly	66	126	**152**	128	74
34.5 in, 35 deg.	76	115	**99**	75	56
-	6	7	8	9	10
Directly	88	182	**217**	182	90
34.5 in., 35 deg.	113	153	**121**	85	57
-	11	12	13	14	15
Directly	84	179	**209**	179	85
34.5 in., 35 deg.	108	149	**117**	84	57

Our measurements in Table 6.2 show that when the light source illuminates the grid from the side (simulating the lights being mounted on the communication tower),

the intensity of light at the center of the grid is less compared to the readings when the light source is directly in front of the wall. We need the intensity to be less to avoid specular reflections on the trains, which were observed on the trains when the RL100-AI50 was temporarily mounted at the site.

Specular reflection occurs when incident light is reflected at the angle of incidence. This phenomenon can be observed especially when light is incident on glossy or shiny surfaces. Most, if not all, containers on the IM trains are painted with a glossy type of paint. Specular reflection should be avoided because of the nature of the TMS algorithm - correlation of two consecutive frames. The train moves some distance horizontally between two consecutive frames. However, the specular reflection occurs at the same coordinates of each frame. When TMS correlates two consecutive frames, it will find that the part of the train that appears near the specularity in the current frame is now moved horizontally in the next frame. There will be a different part of the train appearing near the specularity in the next frame. This will result in inaccurate correlation calculations, and thus degrade TMS performance.

In order to avoid specular reflections and also capture 'bug-free' videos, we conclude that mounting the lights on the communication tower would be better. This will allow TMS to perform a better analysis of train videos. However, to confirm our conclusion that the mounting of lights on the communication tower will avoid specularity, we perform another experiment with lights. We discuss the procedure and results of this experiment next.

Experiment 2: Orientation of Lights to Reduce Specular Reflection

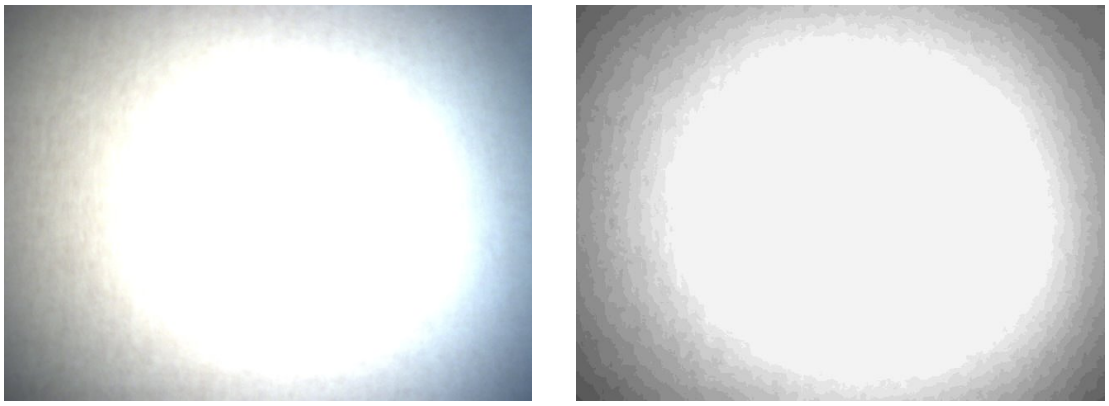
In addition to proposing that the lights should be mounted on the communication tower, we also hypothesize that the lights cannot be aimed directly at the train, as this would again cause specularity. The lights may have to be angled in order to avoid specular reflections for the reasons describe in Experiment 1, above. In order

to test our hypothesis, we perform another experiment by projecting a light on the wall in several orientations, and use the camera to measure the light reflected back, instead of the light projected toward the wall. We capture a still image and feed this image into MATLAB code to create a map of the spread of light. First, we describe the MATLAB code. Next, the various orientations of light will be described with the input and the output map images shown. Finally, the results will be analyzed.

We write MATLAB code so that an input image is converted to an output intensity map to allow us to more easily see how evenly the light is being distributed. The user sets the number of bins (how many categories) for the output image. The input image is turned into a gray-scale image. Then, each pixel of the input image is mapped to one of the bins based on its intensity. There are a total of 256 intensities in a gray-scale image. Each pixel is classified into one of the bins by just checking if it is in the particular interval of intensities for each bin. If it is in the particular interval, then the mapping for that pixel value is just the lower threshold value for that particular interval. In other words, each pixel's intensity is quantized to a certain value based on which ever bin range it fits into. The output image shows a map of the intensities of each pixel in its bin. Please refer to Appendix G for the MATLAB code.

We now discuss the procedure for image capturing. Since it is impossible to have a stationery train at the site to experiment with, we shine a light on the wall in the hallway outside the laboratory in Beckman Institute. First a light is placed so that it simulates the light being mounted on the camera tower in the site. The input and output images are shown in Figure 6.7. This confirms our conclusion from our previous experiment that mounting the light on the camera tower is undesirable because it would clearly create a specularity on the surface of the train.

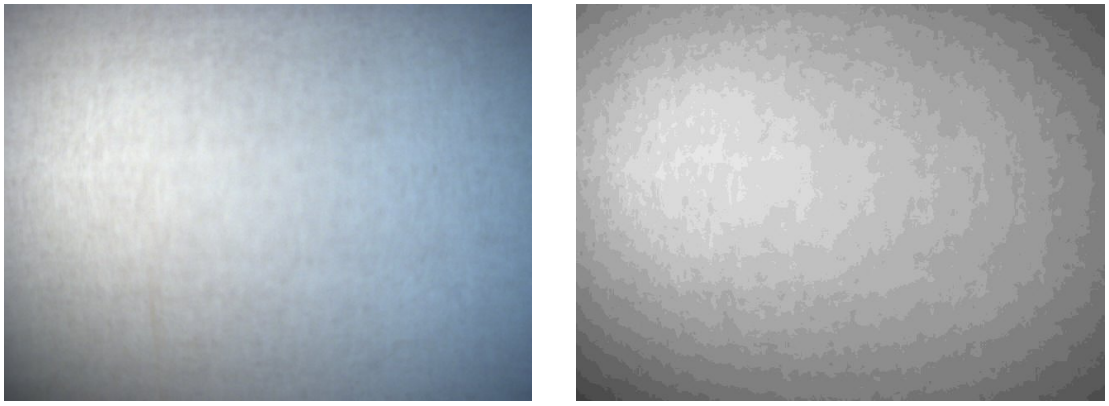
In the orientations described from this point, the light will be on one side of the camera, simulating the lights being mounted on the communication tower. We compare the light intensity mappings after all orientations have been described. Next,



(a) Input Image (b) Output Image

Figure 6.7: Light directly aimed at wall

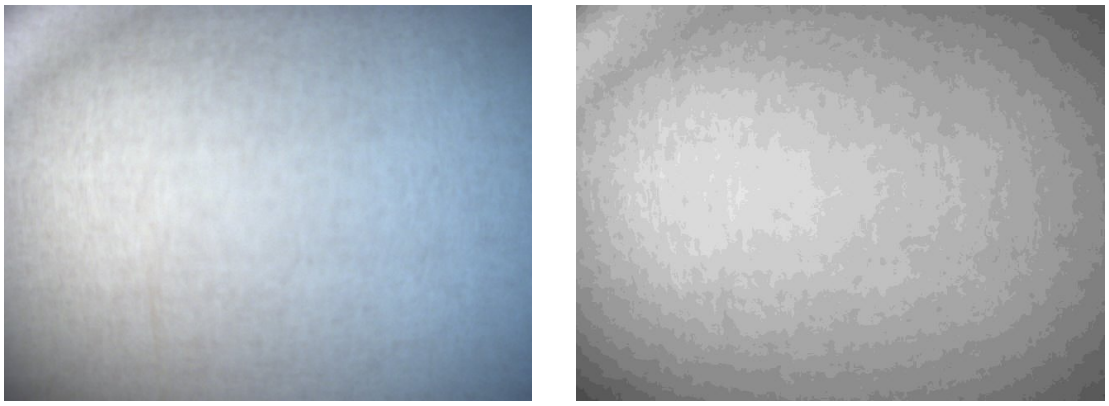
one light is projected directly on to the wall from one side of the camera. The input and output images of this set-up are shown in Figure 6.8.



(a) Input Image (b) Output Image

Figure 6.8: Light from one side aimed at the wall

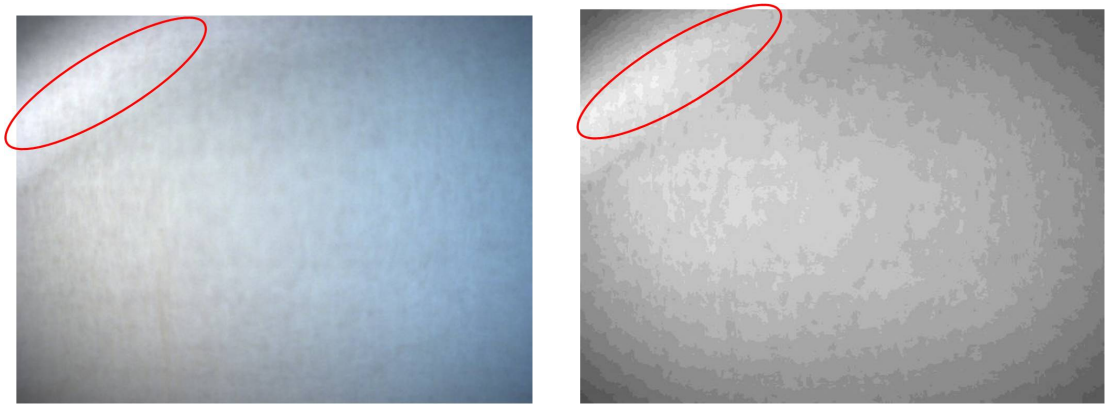
Then, the light source is directed such that some of the light shines on the wall and some on the floor. This orientation also simulates the lights being mounted on the communication tower in the site. However, the lights would be aimed so that they are partially shining on the train and partly on the ground, also known as indirect lighting. This orientation is tested because light incident on the train after diffuse reflections from the ground are less likely to result in strong specular reflections. The input and output images of this orientation is shown in Figure 6.9.



(a) Input Image (b) Output Image

Figure 6.9: Light from one side partially on the floor

The light is then oriented so that it is shining on the floor mainly. This also simulates the lights being on the communication tower, but shining on the ground. The input and output images of this orientation are shown in Figure 6.10. The effect of light marked by the red circles on Figure 6.10 should be discounted as light escaped from the gap between the light and the diffuser. This would not be a problem in lights purchased for the site as the diffuser is fixed completely to the light, without any gaps in between.



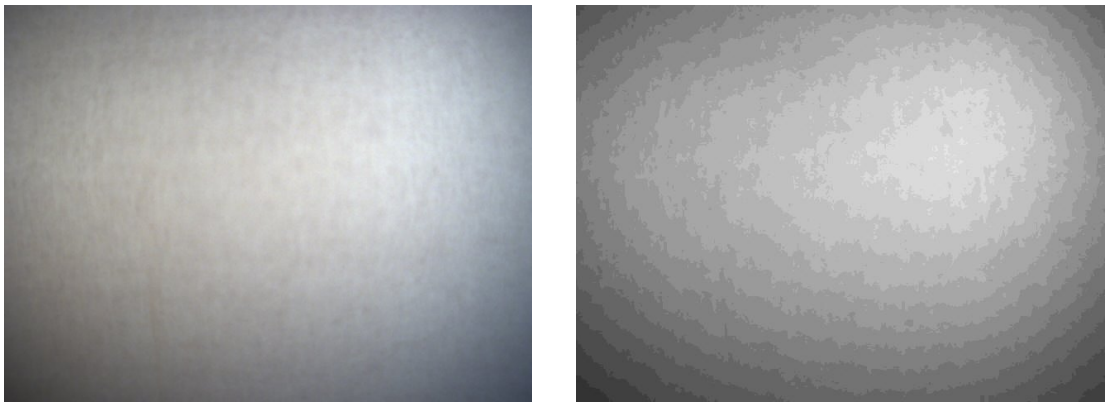
(a) Input Image (b) Output Image

Figure 6.10: Light from one side mainly on the floor

While performing the experiment, we realized that there is an equipment bungalow on the other side of the camera (see Figure 2.1). The bungalow could also be used

to mount the lights. Hence, we wish to see the if specularity can be reduced/avoided and if even illumination can be achieved if we mount some of the lights on the communication tower as well as on the bungalow. The following orientations of lighting will have one light on either side of the camera, simulating lights being mounted on both the communication tower and bungalow.

Figure 6.11 shows the input and output images of both lights shining directly on the wall. We do not clearly see the effect of both lights because one of the lights was placed farther from the camera than the other, to simulate the fact that the communication tower is farther away from the camera than the bungalow.

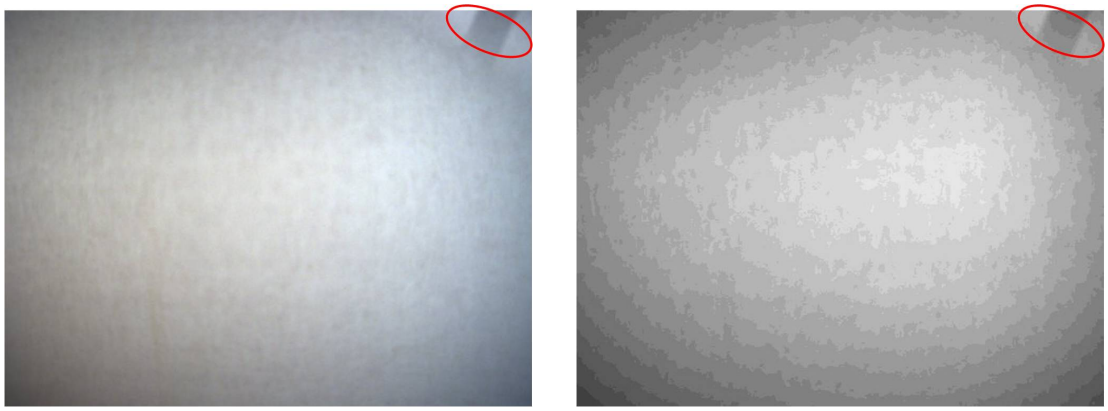


(a) Input Image (b) Output Image

Figure 6.11: Light from both sides aimed on the wall

Next, both lights are aimed on the floor. The rationale for this is the same as explained above for the one light configuration - that reflected light from the ground would reduce specular reflection. Figure 6.12 shows the input and output images of both lights shining on the floor. Again, the effect of light marked by the red circles on Figure 6.12 should be discounted as light escaped from the gap between the light and the diffuser.

From the map images in Figures 6.8 to 6.12, we infer that mounting the lights on the communication tower alone, with them aimed partially on the ground or mainly on the ground, would reduce the specular reflection as much as possible.



(a) Input Image (b) Output Image

Figure 6.12: Light from both sides aimed on the floor

Also, this orientation should produce even illumination across the scene as the ovals corresponding to the different bins in the map images are broader. We prove our hypothesis, that even if the lights are mounted on the communication tower, they should not be directly projected on the train as a specular reflection would occur.

6.4 Conclusions on Lighting Design

We have described all the considerations/requirements, groundwork completed and our initial conclusions for lighting design for the site. Both Raytec's and Holophane's lights are equally expensive. Hence, we have the option of choosing lighting from either of these companies. Concerning the mounting of the lights, they should be mounted on the communication tower aimed towards the floor/ground. This would avoid or reduce the specular reflection on the trains, by providing indirect lighting, which produced a more diffused light, thus fewer specularities.

However, these experiments have all been performed in the lab, where the lights were projected on the wall. Unlike the surfaces of the containers on the train, the wall is not a shiny surface. The ground in the site is made up of rocks and dirt. Hence, the ground would not reflect as much light as a shiny floor made up of waxed

tiles would reflect (like in the lab). In addition, the lights and were not placed at the exact distances and heights shown in the site map (Figure 2.1). Hence, the results from these experiments performed in lab to infer a good lighting design will provide a good starting point, when installing the lighting at the site. From this, the actual lighting at the site should be customized based on results of TMS processing on the train videos captured using the lighting design described above.

CHAPTER 7

CONCLUSION AND FUTURE WORK

Machine vision techniques are now being used to determine the loading pattern on IM freight trains [7]. The train's loading pattern influences its aerodynamic characteristics and consequently its fuel consumption. By optimizing the loading pattern, it is possible to minimize fuel consumption.

BNSF sponsored our group to develop a wayside MV system in Sibley, MO, that determines the loading pattern of passing by IM freight trains. Our machine vision system first captures the videos of trains. The videos are then analyzed using the TMS and TSS algorithms. Each railcar in the train video is given a score for loading efficiency and the entire train video is given an aerodynamic score. Currently, the MV system records videos only during the daytime. However, some of these videos are processed incorrectly by TMS. We analyzed the requirements of the TMS algorithm and improved TMS's performance on daytime trains. Further, to enable nighttime video recording and analysis, we have designed a lighting system to sufficiently illuminate the passing trains. In the paragraphs that follow, we summarize the challenges and solutions in both areas.

The first problem that we encountered came in the context of daytime videos when TMS performed incorrect segmentation leading to background removal errors. To solve this problem, we tried to find some correlation between videos with TMS errors and the average intensity of a white and black square from the ROI on the checkerboard target. We found that the video intensity fluctuated significantly and that TMS incorrectly segmented videos when the mean intensity of a white square

on the sample checkerboard target exceeded the median value. In addition, in some cases, incorrect segmentation occurred because TMS confused the foreground with background (e.g. a blue container against a blue sky). Further, some videos gradually transitioned (faded) from being normally exposed to being over- or under-exposed.

Among these problems, we first set out to determine the cause of fading in train videos. After considerable experimentation, we determined that the motor that operates the camera's aperture caused the fading. The motor responded too slowly to the values set for the aperture's diameter. When this operation happens close to when video capture is to be started, the iris diameter may in fact be changing even as a train video is being acquired. To work around this problem, we adjusted the camera settings every 15 minutes, instead of doing so only when an incoming train triggers the MV system. This non-realtime adjustment of the camera significantly reduced the amount of fading in newly acquired train videos.

After solving the problem of over- and under-exposed videos, we next looked for ways to mitigate the problem of target intensity fluctuations. As mentioned in Section 2.2, the camera's exposure time and iris diameter are adjusted in auto-mode for 5 seconds after the incoming train triggers the MV system. After these 5 seconds, auto-mode is turned off and the exposure time and iris diameter size are set to their instantaneous value just prior to auto mode being disabled. A plot of the evolving exposure time and iris size during the 5 second windows shows that they are somewhat periodic. Ideally, we would expect these curves to follow some monotonic function that asymptotically approaches the final value. Since the auto-mode shut-off-time (i.e. 5 s) is arbitrary, the final exposure time and iris size are also arbitrary. This, in turn, results in brighter or darker images or observed fluctuations in target intensity. To mitigate this problem, we decided to set the exposure and iris size to their time-average value for the 5 second interval before auto-mode is disabled.

To verify that the intensity fluctuations discussed above had indeed been dampened,

we plotted the average intensity of a white and black square from the ROI. The graphs showed that the fluctuation had been considerably reduced. The maximum average value of the white square was ∼0.9, the minimum, excluding outliers, was ∼0.5, and the median ∼0.7. By setting the exposure and iris size to their time-averaged values, the average intensity of the white square has been restricted to a range of values between 0.5 and 0.9, as opposed to between 0.2 and 0.95 earlier. For the case of black squares, the maximum average value was ∼0.25, the minimum, excluding outliers, was ∼0.1, and the median ∼0.2. By setting the exposure and iris size to their time-averaged values, the average intensity of the black square has now been restricted to a range of values between 0.1 and 0.25, very close to the range of averages between 0.03 and 0.17 achieved earlier. Hence, the non-realtime target adjustment and the averaging of the fluctuating camera settings together helped solve the exposure fading and reduce the frequency of the observed errors respectively in TMS results.

The final problem with daytime videos that we addressed involved segmentation errors involving confusion of the background with the foreground. To solve this problem, it is important to improve the contrast between the foreground and background before the other tasks in TMS are performed. Histogram equalization is a common image-processing technique for contrast enhancement in an image. We applied that technique here on a frame-by-frame basis in train videos. To verify this technique's performance, we reprocessed our old videos with a new version of TMS (which now includes histogram equalization). This yielded significant improvement in background removal when compared to videos processed with TMS without histogram equalization.

During our research, we also hypothesized that histogram equalization might help in dampening the intensity fluctuation (problem discussed earlier). Performing histogram equalization on the original image prevents clustering of pixel intensities. To confirm our hypothesis, we ran MATLAB's built-in histogram equalization function

on the single frames from the initial video set. We then calculated the average intensity of a black and white square from the ROI. The old and new average intensities of both the white and black squares were plotted, as shown in Figures 4.9 and 4.10. From these graphs, we saw that the fluctuation of the average intensity of the white and black squares had dampened. There were several places in the graph where the change in the average intensity of the white square was more gradual than before.

We have seen that histogram equalization reduces intensity fluctuations and improves background removal. It is now a standard part of our TMS algorithm implementation. We finally proceeded to use the new TMS to process a new set of videos acquired over several days. Out of 77 videos, 30 trains had perfect TMS results. Minor background removal problems could be seen in 42 videos. However, to our delight, segmentation errors due to background-foreground confusion were not seen in these results. The remaining five videos had major background over-subtraction errors largely because these train videos were acquired at either dawn or dusk. Insufficient lighting at these times resulted in darker-than-preferred videos. We plan to solve this problem with proper artificial lighting near the MV system.

As mentioned earlier, videos captured at dawn or dusk could not be processed adequately by TMS due to insufficient lighting. This is also a problem with nighttime trains. To overcome this fundamental problem with acquiring low-natural-light videos, we decided to design a lighting sub-system for the site. First, in spite of their higher cost, we believe LED lights are best because of their long lifetime (in comparison with halogen lamps). These can be purchased, for example, from Raytec, Inc., at a cost of about \$750 per unit (Qty = 5 required). A third option for lighting is based on high-pressure-sodium lamps from Holophane (Predator model, Qty = 4 required) at a cost of \$825 per unit. Since Holophane lights do not instantly turn on to full brightness, they will have to be turned on if the natural lighting intensity dips below a certain threshold. This would avoid the problem of changing illumination

while a video is being captured.

We also conducted lab experiments to determine the optimal mounting location and orientation for lighting such that the acquired videos are bright enough for TMS-based processing. We concluded that the lights should be aimed partially on the ground to provide indirect lighting and to avoid specular reflection from the surface of the trains. They should also be mounted on a nearby communication tower to avoid attracting bugs around the camera. Further modeling (based on exact choice of light-type) will be required before final installation at the site. However, in this thesis, we have laid the groundwork for the lighting sub-system that will enable nighttime video acquisition and 24/7 operation of the MV system for significant reduction in fuel consumption in IM freight trains.

APPENDIX A

CCD CAMERA PHYSICS AND DESCRIPTIONS OF CAMERA PROPERTIES

A.1 Fundamental Physics of a CCD Camera

The DragonFly2 CCD camera from Point Grey Research is used to capture train videos. It consists of light-collecting optics and an integrated circuit containing light sensitive electronic cells. Each of these rectangular or square shaped cells represents a picture element or pixel in the final image. These cells collect the incident light radiated from the scene and convert them to an electric charge that is read out. Even if the sensors are hit with light from the entire spectrum, the final image is a black and white image. In order to obtain a color image, these sensors are covered with either a red, green, or blue filter. Most commercial CCD cameras use a Bayer filter pattern for this purpose. Figure A.1 shows a CCD image sensor with a Bayer filter on top. As a result, we see an image as shown in the Figure A.2. The unknown values for each of the red, green, and blue images are found using an interpolation technique using the surrounding values. Now, we have three images, known as the red channel, green channel, and blue channel. The pixel values from each of these three channels are put together to obtain the final color image [19]. For instance, when looking at the value of a certain pixel in a color image, we will get three values. These values represent the values of the Red, Green and Blue images. The RGB value for pure red, pure green and pure blue are (255,0,0), (0,255,0), and (0,0,255), respectively. The RGB representations of all the other colors are different combinations of these three.

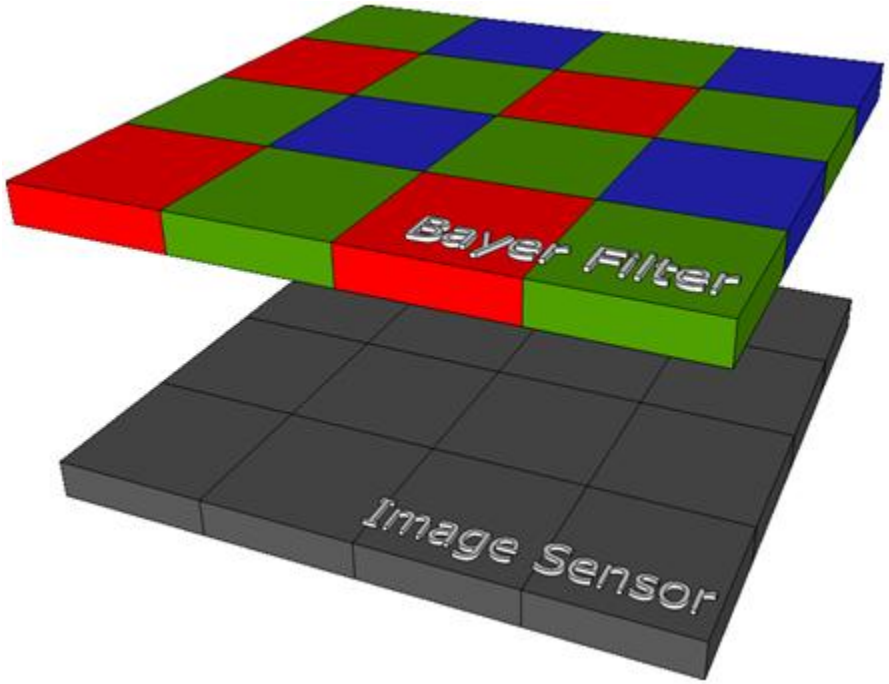


Figure A.1: CCD image sensor and Bayer filter

Figure A.2: Red, green and blue images after Bayer filtering

A.2 DragonFly2 Camera Settings

The camera has the following settings: brightness, exposure, sharpness, saturation, gamma, iris, shutter, and gain, which control how the output image looks. All of these parameters except brightness, hue and gamma have an auto-setting. This means that when the auto-setting is enabled, the values of the settings fluctuate based on the scene, based on the scene, to produce an image that is properly exposed for the current conditions. The following subsections will discuss each of these settings on the camera [20] and their effects on an image. These settings are used in conjunction with the ROI to produce properly exposed videos.

A.2.1 Brightness

The *Commission Internationale de L'Éclairage* (CIE) defines brightness as the attribute of a visual sensation according to which an area appears to emit more or less light [21]. Brightness is measured in percentage (%) and is the level of black in an image. The higher the brightness, the lower the amount of black in the image. In the RGB color space, brightness can be thought of as the average of the red, green, and blue color values.

A.2.2 Exposure

Exposure is the total amount of light that is allowed to fall on the photo-sensor of the camera. Exposure is measured in LUX-seconds and can be calculated from exposure value (EV). EV refers to all combinations of shutter speed and the size of the aperture (iris) that result in the same exposure.

Exposure is closely dependent on the shutter speed. A fast shutter speed results in a short exposure time, while a slow shutter speed amounts to a long exposure time. Exposure is a critical parameter that determines the appearance of the image. Incorrect exposure settings will result in either an under-exposed or over-exposed image. The overall look of an under-exposed image is very dark with details lost in shadow areas of the image. An over-exposed image will look very light with most details 'washed-out'.

A.2.3 Sharpness

Sharpness is the process by which the image is filtered in order to reduce blurred edges in the image. The filter is usually a high-pass filter. This is because information that corresponds to edges in the image is usually stored in the high frequency components. Hence, high-pass filtering the image will perform a sharpening operation on the overall

image.

A.2.4 Saturation

Saturation can be used to produce a monochrome image or an image with vivid colors. When saturation is set to 0, we get a monochrome image. A high saturation value will produce an image with vivid colors. Saturation is a matrix operation. A sample saturation matrix looks like:

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} .299 + .701K & .587(1-K) & .114(1-K) \\ .299(1-K) & .587 + .413K & .114(1-K) \\ .299(1-K) & .587(1-K) & .114 + .886K \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

where R', G' and B' are the modified (saturated) RGB coordinates, and R, G, B are the original (non-saturated) RGB coordinates. K is the saturation factor. If K is 0, the output image will be a monochrome image. If K is 1, there will be no change to the original image. If K is greater than 1, then the output image will be saturated. K less than 0 will yield an image in which the colors are inverted. Figure A.3 illustrates the effect of different values for the saturation factor on the original image.

A.2.5 Gamma

The human vision system has a non-uniform perceptual response to intensity. Hence, gamma correction is needed so that the human eye perceives intensities as intended [21]. Gamma correction controls the overall brightness of an image. As a result, the gamma value can really change the appearance of an image. This is illustrated in Figure A.4. Gamma can be useful in emphasizing the dark or light regions in an

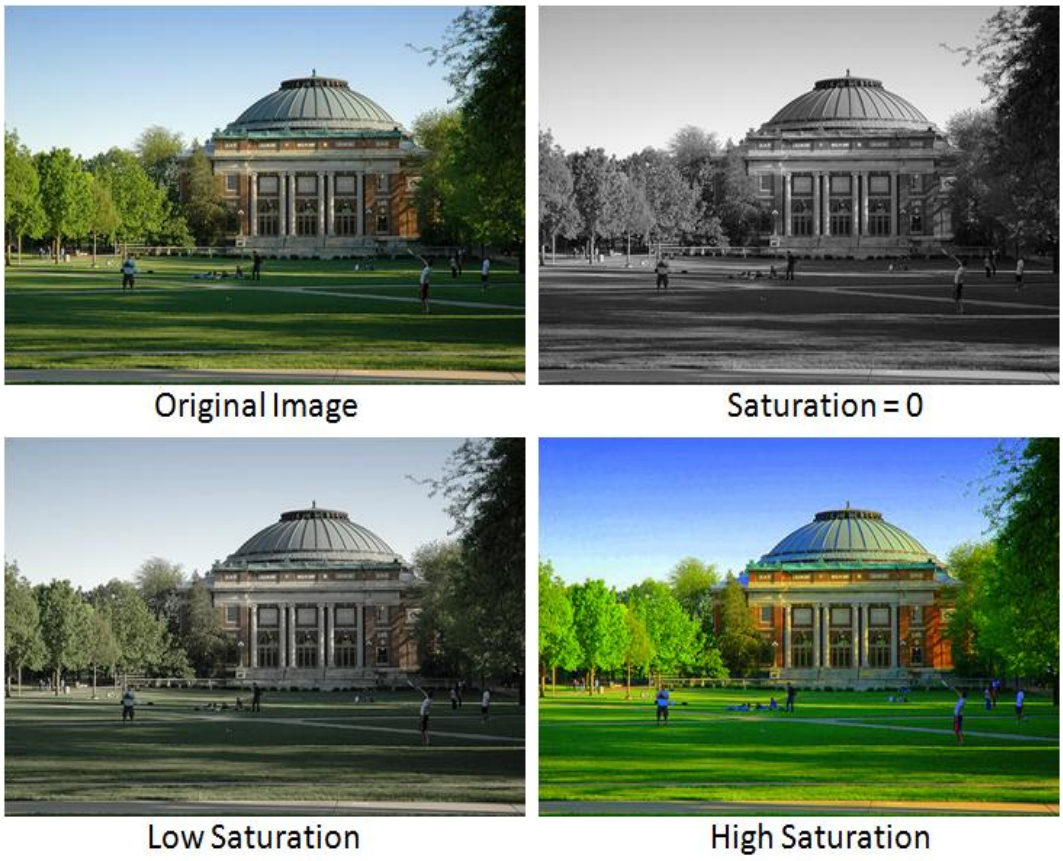


Figure A.3: Effect of different saturation factors on the original image

image. Gamma correction is a function as defined below:

$$I' = AI^{\gamma}$$

where I' is the output pixel intensity, A is a constant, I is the input pixel intensity, and γ is the gamma correction factor. The function is camera dependent. Some cameras might keep the blacks the same, but non-linearly map the greys and white. Others might keep both the white and black constant, but non-linearly map the grey levels in the middle. On the DragonFly2 camera, gamma values greater than 1 lighten the image while gamma values less than 1 darken the image.

Figure A.4: Effect of different gamma values on the original image [22]

A.2.6 Iris

Iris is a measure how open or closed the camera's aperture is. More light hits the camera's photosensors if the iris value is high on the DragonFly2 camera.

A.2.7 Shutter

Shutter is measured in milliseconds, and is the amount of time that the camera's shutter remains open. It is also the integration time for each frame. Long integration time amounts to long exposure time. The shutter speed is an important parameter as a long integration time will cause motion blur when capturing moving objects. The effect of different shutter speeds on flowing water is illustrated in Figure A.5. The shutter speed decreases from the left-most to the right-most images. We can see the drops of water clearly in the right-most image, whereas in the left-most, the falling water is not as clear.

A.2.8 Gain

Gain, unlike gamma, is a linear operation that amplifies the pixel values by multiplying the pixel value by the gain constant. However, if there is noise present in the image, then the noise will also be amplified. Hence, one should be very careful when utilizing gain to enhance an image.

Figure A.5: Effect of different shutter values on flowing water

APPENDIX B

REVIEW OF SEGMENTATION ALGORITHMS

Foreground segmentation is a classic problem in CV. Segmentation methods are typically based on templates, Gaussian mixture models (GMM), energy minimization, and edge detection. However, these methods fail to perform well for our problem which involves segmenting the train in a video to remove the background. In the following sections, we briefly describe each of these segmentation methods reviewed for this application and explain why they are not suitable for our problem [23].

B.1 Template Matching

In this approach, a template of the background is stored before the train enters the field of view of the camera. Each frame in the video can then be subtracted from the template background. The difference can be thresholded to obtain the foreground. However, in our case, changes in the background, such as the movement of clouds, could occur as the video is captured. This could lead to a considerable difference between the stored template background and the actual background appearing in frames towards the end of the video. As a result, it is hard to determine and set the threshold value for obtaining the foreground. Template based segmentation will therefore not accurately segment the foreground for our specific problem.

B.2 Gaussian Mixture Model

A mixture of Gaussians is maintained at each pixel and classifies the pixel in the current frame as belonging to either the foreground or background Gaussian [24]. However, in our case, the containers can be close in color to the background. Hence, there is a risk of containers being confused for the background and vice-versa. Wrong classification of pixels will affect edge detection and load classification that is later performed by TMS. This method was actually implemented as the segmentation technique in TMS. Figure B.1 shows the results from GMM based segmentation and the current segmentation technique as described in Section 2.3.

Scene Types
Day (more illumination)
Evening (less illumination)
Clear Blue Sky
Bright Sunlight (reflection by containers)
Heavy Clouds (static)
Heavy Clouds (moving due to windy day)
Rainy Day (water on lens)
Heavy Clouds (static)
Heavy Clouds (moving due to windy day)
An Image Frame from the Video
GMM Method
Our Proposed Method

Figure B.1: Comparison between GMM and current technique for segmentation [23]

B.3 Energy Minimization

Energy minimization through the graph cut method [25] results in highly accurate segmentation, but is extremely time-consuming. Since we require a fast system to

process our videos, we chose not to follow this method and traded-off accuracy for processing speed.

B.4 Edge Detection

Since the box-shaped loads are projected as rectangles in the video, the loads can be categorized by a top edge and two vertical edges on either side [26]. Hence, the edge features of the containers could be used to segment the video. However, the edges detected by this method are not always meaningful edges. This method also requires setting of a few parameters, which again cannot be appropriately set due to varying weather conditions.

B.5 Selection of Segmentation Algorithm

Among all the above tasks performed by TMS, segmentation of the train, or background removal, is the most critical one. This task determines the performance of all other tasks. Hence, we discuss the final selection of segmentation algorithm for our application. A few other common segmentation algorithms have been discussed earlier in this appendix along with the reasons why they would not work for our application.

Accurate segmentation of the train has the following constraints:

- The train videos are captured all through the year. Hence, the weather conditions vary.
- There may be slight illumination changes due to movement of clouds.
- The system must be efficient time-wise. Each train is captured in 10-15 videos each consisting of 1024 frames. The number of trains captured can be as high

as 10 in a day. Hence, the system needs to be efficient in processing these videos quickly.

After careful consideration of the four algorithms to perform segmentation, we decided to implement the approach that is currently being used by TMS (described in Chapter 2). First, unlike other methods, the method that has currently been implemented does not require the setting of parameters for which an estimate cannot be guessed. Next, this method updates the background template for each frame. This update of the background will adapt to the change in the background over the course of the video, and thus result in accurate background subtraction. This is exactly what we need as the performance of subsequent tasks of TMS depends on the performance of the segmentation algorithm. In addition, this method is fast enough in processing the videos.

APPENDIX C

INTERMEDIATE TMS RESULTS ANALYSIS ON INITIAL SET OF VIDEOS

Table C.1 contains the intermediate TMS result analysis for an old set of videos, as mentioned in Chapter 3.

Table C.1: Intermediate TMS Result Analysis on Old Set of Videos

Train	**TMS Results**	**Color of target**	**Comments**	**Reason for failure of TMS**	**Sky color**	**Lights**
color[2011 22 11][16 08]	Bad	Normal White	Background under subtraction between containers; background over subtraction in containers	Video looks slightly dark than usual	Light Blue sunset	
color[2011 23 11][10 34]	Good	Normal White	background over subtraction in gray UPS containers			
color[2011 23 11][10 49]	Good	Normal White	background over subtraction in one container; consecutive trailers detected as on			
color[2011 23 11][13 39]	Moderate	Normal White (slight yellow tinge)	background over subtraction in containers			
color[2011 23 11][15 40]	Moderate	Peach	background over subtraction in containers; consecutive trailers detected as one			Lights on
color[2011 24 11][10 11]	Bad	Normal White	background over subtraction in many containers			
color[2011 24 11][11 34]	Bad	Normal White	background over subtraction in many containers			
color[2011 24 11][12 20]	Overall Good	Normal White	background over subtraction in few containers			
color[2011 25 11][13 56]		Normal White				
color[2011 25 11][14 38]	Bad	Normal White	background over subtraction in containers; mosaicking errors; may be underexposed as video progresses			
color[2011 25 11][16 58]						
color[2011 26 11][07 35]	Bad		Under exposed			
color[2011 26 11][08 23]	Bad		background over subtraction			
color[2011 26 11][09 11]	Bad		background over subtraction; mosaicking errors			
color[2011 26 11][09 45]						

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2011 26 11][10 44]		Normal White				
color[2011 26 11][11 26]		Normal White				
color[2011 07 12][10 36]	Bad		mosaicking wrong			
color[2011 07 12][10 48]	Bad	White (over-exposed)	background under subtraction. hence wrong edge detection	background subtraction wrong in between containers. Some Blue containers might be close to the sky color.	Sky looks like it is almost night. blue	
color[2011 07 12][16 09]	Overall Good	Pinkish	Over subtraction only in once container			
color[2011 07 12][16 25]	Moderate	Orange-ish	background under subtraction near vertical edge of several containers; background over subtraction in one container			
color[2011 08 12][07 18]	Good	purple-ish (dark)				
color[2011 08 12][07 36]	Moderate	Orange-ish	Background over subtraction in a few containers; few mosaicking errors			
color[2011 08 12][07 49]	Moderate	Orange-ish	Background over subtraction in a few containers; few mosaicking errors; smaller containers in double stacks not detected properly			
color[2011 08 12][08 21]	Moderate	Peach	Background over subtraction in a few containers; few mosaicking errors; smaller containers in double stacks not detected properly			
color[2011 08 12][09 18]	Overall Good	Peach	background under subtraction near vertical edge of several containers;			

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2011 08 12][09 33]	Overall Good	Light Peach	Background over subtraction in a few containers; Mosaicking errors			
color[2011 08 12][10 15]		Light Peach				
color[2011 08 12][10 49]	Bad		background over subtraction in many containers	Several trailers detected as one unit. Over background subtraction in white containers.	Sky looks like it is almost night. blue	
color[2011 14 12][09 43]	Overall Good	Lavender-White	background over subtraction in UPS containers			
color[2011 14 12][09 48]		Whitish-lavender				
color[2011 14 12][10 01]	Overall Good	Whitish-lavender	Consecutive trailers detected as one			
color[2011 14 12][10 10]	Overall Good	Whitish-lavender	Background over subtraction in a few containers			
color[2011 14 12][10 33]		Whitish-lavender				
color[2011 14 12][10 54]	Moderate	Whitish-lavender	Background over subtraction in a few containers; Mosaicking errors			
color[2011 14 12][11 16]	Overall Good	Lavender-White	Background under subtraction at the top of containers; background over subtraction in some containers			
color[2011 14 12][15 44]	Overall Good	Lavender-White	background over subtraction in a few containers			
color[2011 15 12][07 36]	Moderate	Bluish-White	background over subtraction in a few containers; mosaicking errors			
color[2011 15 12][08 13]	Bad	Orange-ish	background over subtraction in containers; mosaicking errors			

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2011 15 12][08 55]	Moderate	Whitish-lavender	background over subtraction in few containers; mosaicking errors			
color[2011 15 12][09 12]	Moderate	Normal White	background over subtraction in a few containers; consecutive trailers detected as one			
color[2011 15 12][09 37]	Bad	Whitish-lavender	background over subtraction in almost all containers; mosaicking errors			
color[2011 15 12][11 05]		Normal White				
color[2011 15 12][11 18]	Bad	Normal White	background over subtraction in most containers; mosaicking errors; consecutive trailers detected as one			
color[2011 15 12][12 59]	Bad	Peach	background over subtraction in many containers	A lot of containers eaten up mostly. Shadow of comm tower seen on containers	Sky looks like it is almost night. blue	Lights on
color[2011 15 12][13 17]	Bad	Peach	Mosaicking errors; background over subtraction			Due to lights
color[2011 15 12][13 25]	Bad	Peach	background over subtraction in containers; mosaicking artifacts	over background subtraction in white containers also. mosaicking artifacts caused by wrong velocity estimation. Shadow of comm Tower seen on containers	Sky looks like it is almost night. blue	Lights on
color[2011 15 12][14 28]	Overall Good	Normal White	background under subtraction			

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2011 15 12][15 43]	Moderate	Peach	background over subtraction in some containers; mosaicking errors; background under subtraction near vertical edges of containers			
color[2011 15 12][16 07]	Bad	Peach	background over subtraction in many containers	Over background subtraction in white and grey containers	medium light blue. sunset	Lights on
color[2011 15 12][16 28]	Overall Good	Orang-ish	background over subtraction in one container			
color[2012 24 01][09 26]	Overall Good	Lavendar-White	background over subtraction in one container			
color[2012 24 01][09 40]	Overall Good	White (over-exposed)	background under subtraction between containers			
color[2012 24 01][10 16]	Overall Good	White (over-exposed)	background over subtraction in few grey UPS containers			
color[2012 24 01][13 02]	Bad	White (over-exposed)	background over subtraction in containers			
color[2012 24 01][13 25]	Good	White (over-exposed)	background under subtraction between one container			
color[2012 24 01][14 31]	Bad	Normal White	background under subtraction at top and between containers			
color[2012 24 01][14 43]		Normal White				
color[2012 24 01][15 09]		Normal White				
color[2012 25 01][14 23]	Bad	Normal White	background under subtraction at top and between few containers; background over subtraction in few containers			
color[2012 27 01][16 55]		Dark				Dark
color[2012 28 01][08 47]	Overall Good	White (over-exposed)	Slight background over subtraction			

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2012 28 01][14 12]	Bad	White (over-exposed)	background over subtraction; first few containers detected as one			
color[2012 28 01][14 58]	Moderate	White (over-exposed)	background over subtraction in some containers			
color[2012 28 01][15 41]	Good	White (over-exposed)	NO PROBLEMS!			
color[2012 28 01][16 30]	Good	White (over-exposed)	NO PROBLEMS!			
color[2012 29 01][09 22]	Bad	White (over-exposed)	background over subtraction in some containers			
color[2012 29 01][09 30]	Overall Good	White (over-exposed)	background over subtraction in few containers; background under subtraction between few containers			
color[2012 29 01][10 11]	Overall Good	White (over-exposed)	background over subtraction in a few containers (esp red)			
color[2012 29 01][11 41]	Moderate	White (over-exposed)	background over subtraction; background under subtraction between containers			
color[2012 29 02][15 58]		White (over-exposed)				
color[2012 01 02][08 45]		Peach (light)				
color[2012 01 02][10 04]	Moderate	Yellow-ish	background over subtraction in some containers			
color[2012 02 02][09 03]	Good	Yellow-ish	NO PROBLEMS!			
color[2012 02 02][09 27]	Good	Yellow-ish	NO PROBLEMS!			
color[2012 02 02][11 21]	Moderate	White (over-exposed)	background over subtraction in some containers			
color[2012 02 02][12 00]						

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2012 02 02][13 07]	Bad	Yellow-ish	background over subtraction in some containers; background under subtraction in many frames			
color[2012 02 02][14 28]	Bad	Light yellow	background under subtraction between containers			
color[2012 02 02][15 19]	Bad	Normal White	background over subtraction in few containers; background under subtraction between containers			
color[2012 02 02][16 32]		Dull White				Sunset
color[2012 03 02][13 26]		Normal White				
color[2012 03 02][15 16]	Bad	Dull White (lavender-ish)	Mosaicking problems; background under subtraction/over subtraction in containers; (maybe underexposed)	Wrong velocity estimation	purplish blue sky.	Dark
color[2012 03 02][15 29]		Dull White				Sunset
color[2012 03 02][16 01]		Lavender-White				
color[2012 03 02][16 09]		Dull White				Sunset
color[2012 03 02][18 26]	Good	Dark Orange	all containers in first frame detected as one	Containers look orange.	Completely dark. Lights are on	
color[2012 03 02][20 38]	Good	Dark Orange	NO PROBLEMS! (motion blur)			
color[2012 03 02][21 23]	Bad	Dark Orange	Under exposed (motion blur)			
color[2012 03 02][22 02]	Moderate	Dark Orange	background over subtraction in a few containers;			
color[2012 04 02][12 04]	Bad	Lavender-White	background over subtraction in every container	Rainy day; water on lens of camera. Reflection from that makes container color close to sky color	White sky	Dark

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2012 05 02][08 56]	Bad	White (overexposed)	background over subtraction in several containers			
color[2012 05 02][09 17]	Moderate	White (overexposed)	background over subtraction in few containers			
color[2012 05 02][10 35]	Bad	White (overexposed)	background over subtraction			
color[2012 05 02][11 23]	Moderate	White (overexposed)	background over subtraction	Over-subtraction in blue containers that are confused for the sky	Deep Blue	
color[2012 05 02][11 29]		White (overexposed)				
color[2012 05 02][11 53]	Bad	White (overexposed)	background over subtraction in several containers	White and red containers	Deep Blue; Video darkens when white containers pass, and brightens when dark containers pass by	
color[2012 05 02][12 21]	Bad	White (overexposed)	background over subtraction in several containers	Blue containers confused with sky; White, green and red containers also affected	Deep Blue; Video darkens when white containers pass, and brightens when dark containers pass by	

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2012 05 02][13 26]	Bad	White (overexposed)	background over subtraction in several containers	White and red containers	Deep Blue; Video darkens when white containers pass, and brightens when dark containers pass by	
color[2012 05 02][13 45]	Bad	White (overexposed)	background over subtraction in several containers	Mostly Blue containers affected; White also	Deep Blue; Video darkens when white containers pass, and brightens when dark containers pass by	
color[2012 05 02][15 11]	Bad	White (overexposed)	background over subtraction			
color[2012 06 02][12 10]		White (overexposed)				
color[2012 06 02][12 26]		White (overexposed)				
color[2012 06 02][13 15]	Bad	White (overexposed)	background over subtraction in every frame; mosaicking errors	Wrong velocity estimation; all color containers affected	Deep Blue; Video darkens when white containers pass, and brightens when dark containers pass by	

Table C.1 : Cont.

Train	TMS Results	Color of target	Comments	Reason for failure of TMS	Sky color	Lights
color[2012 06 02][15 37]	Bad	White (over-exposed)	background over subtraction in every frame	White Containers affected	Deep Blue; Video darkens when white containers pass, and brightens when dark containers pass by	
color[2012 29 02][15 58]						
color[2012 29 02][16 07]	Overall Good	Peach	background over subtraction	White and Grey containers	Deep Blue	
color[2012 01 03][08 14]						
color[2012 01 03][08 21]	Overall Good	Peach	background over subtraction in one container	in White containers also. background under subtraction in between some containers	Bright sunny day	
color[2012 01 03][08 28]						
color[2012 01 03][09 18]	Overall Good	Peach	background over subtraction in one container	Dark blue container	deep blue sky	
color[2012 01 03][09 33]	Moderate	Peach/Normal White	background over subtraction in many containers	In white containers	deep blue sky	
color[2012 01 03][09 53]	Overall Good	Peach/Normal White	background over subtraction in few containers		deep blue sky	
color[2012 01 03][10 38]	Bad	Peach/Normal White	background over subtraction in almost every frame	In white containers	deep blue sky	
color[2012 01 03][12 51]						
color[2012 01 03][13 05]	Good	White (over-exposed)	NO PROBLEMS!		deep blue sky	

APPENDIX D

MATLAB CODE FOR COMPUTING AVERAGE INTENSITY OF EXPOSURE TARGET

The following MATLAB code is used to compute the average intensity of a black and white square from the old ROI.

```
function intensity(img)
%For old target and ROI (December 2011)

figure(1), hold off, imshow(img), hold on, plot(390,425,'r*'), ...
plot(390,454,'r*'), plot(421,425,'r*'), plot(421,454,'r*'), ...
plot(427,425,'g*'), plot(427, 454,'g*'), plot(454, 425,'g*'),  ...
plot(454, 454,'g*'), plot(425,390,'b*'), plot(425,421,'b*'),...
plot(454,390,'b*'), plot(454,421,'b*');

 white = img(425:454, 390:421);  %extracts white square and displays
 figure(2),imshow(white);

black = img(425:454, 427:454);  %extracts black square and displays
figure(3), imshow(black);

White_Avg = mean(mean(white))
Black_Avg = mean(mean(black))
end
```

The following MATLAB code is used to compute the average intensity of a black and white square from the new ROI.

```
function intensity(img)
%For new target starting Jan 2012

figure(1), hold off, imshow(img), hold on, plot(422,455,'r*'), ...
plot(455,455,'r*'), plot(455,479,'r*'), plot(422,479,'r*') ...
     , plot(456,454,'g*'), plot(484, 454,'g*'), plot(484, 480,'g*'),...
 plot(456, 480,'g*');

white = img(455:479, 422:455);     %extracts white square and displays
figure(2),imshow(white);
```

```
black = img(454:480,456:484);   %extracts black square and displays
figure(3), imshow(black);

White_Avg = mean(mean(white))
Black_Avg = mean(mean(black))
end
```

APPENDIX E

ANALYSIS OF INTERMEDIATE TMS RESULTS ON INITIAL VIDEOS WITH HISTOGRAM EQUALIZATION

Table E.1 shows the intermediate TMS result analysis for the old set of videos, with histogram equalization.

Table E.1: Intermediate TMS Result Analysis on Old Set of Videos (With Histogram Equalization)

Train	**Verdict Before**	**Pre-Histogram Equalization TMS Results**	**Verdict After**	**Post Histogram Equalization TMS Results**	**Possible Reason for Bad Results**
color[2011 23 11][10 34]	Good	background over subtraction in gray UPS containers	Good	Grey containers passed! background over subtraction only in ONE white container!	
color[2011 24 11][10 11]	Bad	background over subtraction in many containers	Bad	background over subtraction in white containers	deep grey sky - No identifiable reason
color[2011 24 11][11 34]	Bad	background over subtraction in many containers	Bad	background over subtraction in white containers	deep grey sky - No identifiable reason
color[2011 25 11][14 38]	Bad	background over subtraction in containers; mosaicking errors; may be underexposed as video progresses	Good	Mosaicking errors; minor background over subtraction in few containers	
color[2011 07 12][10 48]	Bad	background under subtraction. hence wrong edge detection	Good	Major background Over subtraction only 2 blue containers; minor over subtraction in 1-2 white containers	
color[2011 08 12][07 36]	Moderate	Background over subtraction in a few containers; few mosaicking errors	Moderate	background Over subtraction in 1 container; background under subtraction (literally no background subtraction) in between containers in few containers	No identifiable reason
color[2011 08 12][08 21]	Moderate	Background over subtraction in a few containers; few mosaicking errors	Good	NO PROBLEMS! Perfect background subtraction.	
color[2011 14 12][11 16]	Overall Good	Background under subtraction at the top of containers; background over subtraction in some containers	Good	NO PROBLEMS! Perfect background subtraction.	
color[2011 15 12][11 18]	Bad	background over subtraction in most containers; mosaicking errors	Bad	Major background over subtraction in fewer containers;	Sky was whitish blue - hence white containers affected

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2011 15 12][12 59]	Bad	background over subtraction in many containers	Bad	Major background over subtraction in several containers	No identifiable reason
color[2011 15 12][13 17]	Bad	Mosaicking errors; background over subtraction	Bad	Mosaicking Errors	deep grey sky - No identifiable reason
color[2011 15 12][13 25]	Bad	background over subtraction in containers; mosaicking artifacts	Moderate	Mosaicking Errors; minor background over subtraction in a few containers	
color[2011 15 12][16 07]	Bad	background over subtraction in many containers	Moderate	Minor background over subtraction in 5-6 containers	
color[2012 28 01][15 41]	Good	NO PROBLEMS!	Good	NO PROBLEMS!	
color[2012 28 01][16 30]	Good	NO PROBLEMS!	Good	NO PROBLEMS!	
color[2012 29 01][10 11]	Overall Good	background over subtraction in a few containers (esp red)	Moderate	Minor background over subtraction in few containers	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2012 01 02][10 04]	Moderate	background over subtraction in some containers	Good	Minor background over subtraction in 1-2 containers	
color[2012 02 02][09 03]	Good	NO PROBLEMS!	Good	NO PROBLEMS! Perfect background subtraction.	
color[2012 02 02][09 27]	Good	NO PROBLEMS!	Good	NO PROBLEMS! Perfect background subtraction.	
color[2012 03 02][20 38]	Good	NO PROBLEMS! (motion blur)	Good	NO PROBLEMS! Perfect background subtraction.	
color[2012 03 02][21 23]	Bad	Under exposed (motion blur)	Bad	Motion Blur; mosaicking artifacts	night time video - insufficient lighting
color[2012 04 02][12 04]	Bad	background over subtraction in every container	Bad	Mosaicking artifacts; background over subtraction b/c of glare at top of containers	Sky was whitish blue and glare was also white

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2012 05 02][08 56]	Bad	background over subtraction in several containers	Bad	background over subtraction in a series of consecutive maroon containers	no identifiable reason
color[2012 05 02][09 17]	Moderate	background over subtraction in few containers	Moderate	Minor background over subtraction in a few containers; some blue containers affected	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2012 05 02][10 35]	Bad	background over subtraction	Bad	White containers affected (background over subtraction)	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2012 05 02][11 23]	Moderate	background over subtraction	Overall Good	Minor background over subtraction in blue containers	Sky was very close to the blue color of container
color[2012 05 02][11 53]	Bad	background over subtraction in several containers	Bad	Major background over subtraction in several white containers	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2012 05 02][12 21]	Bad	background over subtraction in several containers	Bad	Minor background over subtraction in few containers (Red, green, blue containers); Major over subtraction in some containers (mostly white)	Fluctuation - video gets darker when a white container comes and brightens when color containers come

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2012 05 02][13 26]	Bad	background over subtraction in several containers	Moderate	background over subtraction in red and white containers; blue containers not bad!	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2012 05 02][13 45]	Bad	background over subtraction in several containers	Bad	Double stacks were fine; major over subtraction in single containers (regardless of color)	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2012 01 03][09 18]	Overall Good	background over subtraction in one container	Good	NO PROBLEMS! Perfect background subtraction in all blue containers	
color[2012 01 03][09 33]	Moderate	background over subtraction in many containers	Good	Minor background over subtraction in white containers	
color[2012 01 03][13 05]	Good	NO PROBLEMS!	Good	NO PROBLEMS! Perfect background subtraction in all blue containers	
color[2012 06 02][15 37]	Bad	background over subtraction in every frame	Bad	White and red containers affected (background over subtraction.) Blue containers were fine	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2011 22 11][16 08]	Bad	background under subtraction between containers; background over subtraction in containers	Moderate	Minor background over subtraction in several containers	
color[2012 01 03][08 21]	Overall Good	background over subtraction in one container	Good	NO PROBLEMS!	

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2012 01 03][09 53]	Overall Good	background over subtraction in few containers	Good	background over subtraction in one white container	
color[2012 01 03][10 38]	Bad	background over subtraction in almost every frame	Bad	background over subtraction in almost all white container	no identifiable reason
color[2012 03 02][15 16]	Bad	Mosaicking PROBLEMS; background under subtraction/over subtraction in containers; (maybe underexposed)	Bad	Mosaicking errors; background under subtraction in between containers	Fluctuation - sky color becomes lighter blue when train is in scene and darkens in between containers
color[2012 03 02][18 26]	Good	all containers in first frame detected as one	Good	NO PROBLEMS!	
color[2012 05 02][11 29]			Good	Minor background over subtraction in red and white containers	
color[2012 06 02][13 15]	Bad	background over subtraction in every frame; mosaicking errors	Bad	Double stacks were fine; major over subtraction in single containers (regardless of color)	Fluctuation - video gets darker when a white container comes and brightens when color containers come
color[2012 29 02][16 07]	Overall Good	background over subtraction in white and grey containers	Overall Good	background over subtraction in one single stack container	
color[2011 07 12][16 09]	Overall Good	Over subtraction only in one container	Good	Minor over subtraction in white containers	
color[2011 07 12][16 25]	Moderate	background under subtraction near vertical edge of several containers; background over subtraction in one container	Overall Good	few Mosaicking errors; minor background over subtraction in white and red containers	
color[2011 08 12][07 18]	Good		Good	NO PROBLEMS!	

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2011 08 12][07 49]	Moderate	Background over subtraction in a few containers; few mosaicking errors; smaller containers in double stacks not detected properly	Good	minor background over subtraction in white and red containers; all blue containers passed!	
color[2011 08 12][09 18]	Overall Good	background under subtraction near vertical edge of several containers;	Good	NO PROBLEMS!	
color[2011 08 12][09 33]	Overall Good	Background over subtraction in a few containers; Mosaicking errors	Good	background over subtraction in few white and grey containers	
color[2012 24 01][09 40]	Overall Good	background under subtraction between containers; mosaicking errors	Overall Good	background under subtraction between containers; mosaicking errors	
color[2012 24 01][10 16]	Overall Good	background over subtraction in few grey UPS containers	Good	minor over subtraction in 2 grey containers	
color[2012 24 01][13 02]	Bad	background over subtraction in containers	Good	Minor over subtraction in white containers	
color[2012 24 01][13 25]	Good	background under subtraction between one container	Good	NO PROBLEMS!	
color[2012 24 01][14 31]	Bad	background under subtraction at top and between containers	Bad	background under subtraction at top and between few containers	
color[2011 14 12][10 01]	Overall Good	NO PROBLEMS!	Good	NO PROBLEMS!	
color[2011 14 12][10 10]	Overall Good	Background over subtraction in a few containers	Bad	background over subtraction. in single stacks	
color[2011 14 12][10 54]	Moderate	Background over subtraction in a few containers; Mosaicking errors	Good	Only 1 place of mosaicking error; background subtraction was fine	
color[2011 14 12][15 44]	Overall Good	background over subtraction in a few containers	Good	minor background over subtraction in 2 white containers	

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2011 15 12][07 36]	Moderate	background over subtraction in a few containers; mosaicking errors	Good	NO PROBLEMS!	
color[2011 15 12][08 13]	Bad	background over subtraction in containers; mosaicking errors	Overall Good	minor background over subtraction in a few white containers; no mosaicking errors	
color[2011 15 12][08 55]	Moderate	background over subtraction in few containers; mosaicking errors	Good	NO PROBLEMS!	
color[2011 15 12][09 12]	Moderate	background over subtraction in a few containers;	Overall Good	background under subtraction in between 2 containers	
color[2011 15 12][09 37]	Bad	background over subtraction in almost all containers; mosaicking errors	Moderate	mosaicking errors; minor background over subtraction in a few containers	
color[2011 15 12][14 28]	Overall Good	background under subtraction	Good	NO PROBLEMS!	
color[2011 15 12][15 43]	Moderate	background over subtraction in some containers; mosaicking errors; background under subtraction near vertical edges of containers	Moderate	minor background over subtraction in some white and red containers; few mosaicking errors; no background subtraction in between containers where mosaicking errors occurred.	
color[2011 15 12][16 28]	Overall Good	background over subtraction in one container	Good	NO PROBLEMS!	
color[2011 23 11][10 49]	Good	background over subtraction in one container	Good	NO PROBLEMS!	
color[2011 23 11][13 39]	Moderate	background over subtraction in containers	Good	NO PROBLEMS!	
color[2011 23 11][15 40]	Moderate	background over subtraction in containers	Good	minor background over subtraction in 2 white containers	

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2011 24 11][12 20]	Overall Good	background over subtraction in few containers	Good	NO PROBLEMS!	
color[2011 25 11][13 56]			Good	NO PROBLEMS!	
color[2011 26 11][10 44]			Good	NO PROBLEMS!	
color[2011 26 11][11 26]			Good	NO PROBLEMS!	
color[2012 02 02][11 21]	Moderate	background over subtraction in some containers	Overall Good	background over subtraction in one whole container	
color[2012 02 02][13 07]	Bad	background over subtraction in some containers; background under subtraction in many frames	Bad	Double stacks were fine; major over subtraction in single containers (regardless of color); no background subtraction between containers in many frames	
color[2012 02 02][14 28]	Bad	background under subtraction between containers	Bad	no background subtraction between few containers	
color[2012 02 02][15 19]	Bad	background over subtraction in few containers; background under subtraction between containers	Bad	no over subtraction PROBLEMS; no background subtraction between few containers	
color[2012 03 02][22 02]	Moderate	background over subtraction in a few containers;	Good	minor background over subtraction in one container	
color[2012 05 02][15 11]	Bad	background over subtraction	Moderate	minor background over subtraction in white and red containers; all blue containers passed!	
color[2012 24 01][10 16]	Overall Good	background over subtraction in few grey UPS containers	Good	NO PROBLEMS!	
color[2012 24 01][15 09]			Good	NO PROBLEMS!	
color[2012 25 01][14 23]	Bad	background under subtraction at top and between few containers; background over subtraction in few containers	Bad	background under subtraction at top and between few containers; no background over subtraction	

Table E.1 : Cont.

Train	Verdict Before	Pre-Histogram Equalization TMS Results	Verdict After	Post Histogram Equalization TMS Results	Possible Reason for Bad Results
color[2012 28 01][14 12]	Bad	background over subtraction	Good	background over subtraction only in one white container	
color[2012 28 01][14 58]	Moderate	background over subtraction in some containers	Moderate	background over subtraction in white and red containers; blue containers passed!	
color[2012 29 01][09 22]	Bad	background over subtraction in some containers	Bad	background over subtraction in white containers	
color[2012 29 01][09 30]	Overall Good	background over subtraction in few containers; background under subtraction between few containers	Good	NO PROBLEMS!	
color[2012 29 01][11 41]	Moderate	background over subtraction; background under subtraction between containers	Moderate	background over subtraction in white containers; background under subtraction fixed	

APPENDIX F

INTERMEDIATE TMS RESULTS FOR THE NEW SET OF VIDEOS

Tables F.1 - F.4 contain a record of the intermediate TMS results for the new set of videos acquired for each variation, as described in Chapters 4 and 5.

Table F.1: Variation I: Intermediate TMS Result Analysis

Train	**Verdict**	**Comments**
color[2012 08 07][13 21]	Overall good	background over subtraction into halfway from top of 3 red containers; minor background over subtraction in 2 white containers
color[2012 08 07][17 05]	Bad	minor background over subtraction in every container; background under subtraction in between containers in a few places
color[2012 08 07][17 33]	Good	background over subtraction in 2 single stack green containers; all blue containers passed!
color[2012 08 07][19 33]	Good	Perfect! NO PROBLEMS!
color[2012 08 07][20 08]	Bad	background under subtraction at top of many containers (looks like double stack); background over subtraction in a few containers
color[2012 09 07][07 43]	Good	minor background over subtraction in 3 white containers
color[2012 09 07][07 56]	Overall good	minor background over subtraction in few white containers
color[2012 09 07][10 20]	Bad	Major background over subtraction in 10 containers

Table F.2: Variation II: Intermediate TMS Result Analysis

Train	Verdict	Comments
color[2012 09 07][14 45]	Good	background over subtraction in one red container; All blue containers passed!
color[2012 09 07][16 27]	Moderate	major background over subtraction in a few white containers
color[2012 09 07][18 07]	Good	Perfect! NO PROBLEMS!
color[2012 09 07][19 43]	Overall Good	major background over subtraction in 4 white containers; all blue containers passed!
color[2012 10 07][08 32]	Good	Perfect! NO PROBLEMS!
color[2012 10 07][10 38]	Good	Perfect! NO PROBLEMS!; All blue containers passed!
color[2012 10 07][12 14]	Good	Perfect! NO PROBLEMS!
color[2012 10 07][17 47]	Bad	Major background over subtraction in all white containers
color[2012 10 07][18 00]	Good	Perfect! NO PROBLEMS!
color[2012 11 07][18 42]	Bad	Overexposed video
color[2012 12 07][06 55]	Moderate	background over subtraction in a few containers
color[2012 12 07][07 51]	Good	background over subtraction in 2 white containers
color[2012 12 07][10 38]	Overall Good	minor background over subtraction in few white and 1 red containers
color[2012 12 07][10 49]	Good	Perfect! NO PROBLEMS!
color[2012 12 07][11 57]	Good	background over subtraction in 3 containers;
color[2012 12 07][12 58]	Good	Minor background over subtraction in few containers
color[2012 12 07][13 35]	Moderate	background over subtraction in few containers

Table F.3: Variation III: Intermediate TMS Result Analysis

Train	Verdict	Comments
color[2012 12 07][15 34]	Good	Perfect! NO PROBLEMS!
color[2012 12 07][16 12]	Good	Perfect! NO PROBLEMS!
color[2012 12 07][16 37]	Moderate	Minor background over subtraction in white containers
color[2012 12 07][17 32]	Good	Perfect! NO PROBLEMS!
color[2012 12 07][17 43]	Bad	Major background over subtraction in several containers
color[2012 12 07][20 25]	Good	Perfect! NO PROBLEMS!
color[2012 13 07][06 07]	Bad	Major background over subtraction in several containers; background under subtraction in between containers in few places
color[2012 13 07][07 12]		
color[2012 13 07][10 53]	Overall Good	minor background over subtraction in few white containers
color[2012 13 07][13 38]	Overall Good	minor background over subtraction in few white containers
color[2012 13 07][18 13]	Good	Perfect! NO PROBLEMS!
color[2012 13 07][18 27]	Good	Perfect! NO PROBLEMS!
color[2012 13 07][18 43]	Good	background over subtraction in 3 containers
color[2012 13 07][19 31]	Overall Good	background over subtraction in single stack containers
color[2012 14 07][07 47]	Good	minor background over subtraction in 2 green containers
color[2012 14 07][08 55]	Moderate	Major background over subtraction in single stack white containers; background under subtraction in between containers in a few places
color[2012 14 07][09 12]	Good	Perfect! NO PROBLEMS!
color[2012 14 07][09 34]	Good	Perfect! NO PROBLEMS!
color[2012 14 07][09 52]	Good	Perfect! NO PROBLEMS!; All blue containers passed!
color[2012 14 07][10 10]	Good	Perfect! NO PROBLEMS!
color[2012 14 07][10 25]	Good	minor background over subtraction in few white containers
color[2012 14 07][10 38]	Moderate	Major background over subtraction in several containers
color[2012 14 07][11 48]	Overall Good	background over subtraction in few containers
color[2012 14 07][12 20]	Moderate	Major background over subtraction in several white containers
color[2012 14 07][14 37]	Good	Major background over subtraction in 2 containers
color[2012 14 07][15 09]	Bad	Major background over subtraction in several containers
color]2012 14 07][16 11]	Bad	Major background over subtraction in several containers
color[2012 14 07][17 43]	Good	Perfect! NO PROBLEMS!
color[2012 14 07][18 13]	Good	background over subtraction in 3 containers
color[2012 14 07][19 07]	Good	Major background over subtraction in 1 white container
color[2012 14 07][19 21]	Good	Perfect! NO PROBLEMS!; All blue containers passed!

Table F.3 : Cont.

Train	Verdict	Comments
color[2012 14 07][19 35]	Bad	Major background over subtraction in almost every container

Table F.4: Variation IV: Intermediate TMS Result Analysis

Train	Verdict	Comments
color[2012 15 07][12 55]	Bad	Major background over subtraction in several containers
color[2012 15 07][13 07]	Good	Perfect! NO PROBLEMS!
color[2012 15 07][15 57]	Good	Perfect! NO PROBLEMS!; All blue containers passed!
color[2012 15 07][16 45]	Good	background over subtraction in one container
color[2012 15 07][18 05]	Moderate	Major background over subtraction in few containers
color[2012 15 07][18 16]	Good	Perfect! NO PROBLEMS!
color[2012 16 07][06 03]	Bad	Major background over subtraction in few containers
color[2012 16 07][07 33]	Good	Perfect! NO PROBLEMS!
color[2012 16 07][07 49]	Good	Perfect! NO PROBLEMS!
color[2012 16 07][07 59]	Good	Perfect! NO PROBLEMS!
color[2012 16 07][09 35]	Good	Major background over subtraction in 2 containers
color[2012 16 07][10 56]	Bad	background over subtraction in several containers; minor over subtraction in few containers
color[2012 16 07][11 12]	Good	Major background over subtraction in 2 containers
color[2012 16 07][12 35]	Good	background over subtraction in 1 container
color[2012 16 07][13 01]	Good	Minor background over subtraction in few containers
color[2012 16 07][17 23]	Good	Perfect! NO PROBLEMS!; All blue containers passed!
color[2012 16 07][17 39]	Good	Minor background over subtraction in 2 containers
color[2012 16 07][19 03]	Good	background over subtraction in 1 container
color[2012 16 07][20 12]	Good	background over subtraction in 2 single stack blue containers
color[2012 16 07][20 31]	Good	Perfect! NO PROBLEMS!
color[2012 17 07][06 47]	Overall Good	background over subtraction in 4 single stack containers
color[2012 17 07][09 27]	Good	Perfect! NO PROBLEMS!
color[2012 17 07][12 04]	Overall Good	background over subtraction in 4 containers
color[2012 17 07][14 47]	Good	Perfect! NO PROBLEMS!
color[2012 17 07][18 53]	Good	background over subtraction in 2 containers
color[2012 18 07][06 31]	Good	background over subtraction in 1 container
color[2012 18 07][06 43]	Good	background over subtraction in 2 single stack containers
color[2012 18 07][08 17]	Good	Perfect! NO PROBLEMS!
color[2012 18 07][08 38]	Good	background over subtraction in 2 containers
color[2012 18 07][11 12]	Good	background over subtraction in 3 containers
color[2012 18 07][11 35]	Good	Perfect! NO PROBLEMS!
color[2012 18 07][19 27]	Good	Perfect! NO PROBLEMS!
color[2012 19 07][16 38]	Good	Minor background over subtraction in 1 container
color[2012 19 07][17 04]	Good	Perfect! NO PROBLEMS!
color[2012 20 07][08 54]	Good	Perfect! NO PROBLEMS!
color[2012 20 07][09 10]	Good	Major background over subtraction in 1 container
color[2012 20 07][09 25]	Good	Perfect! NO PROBLEMS!
color[2012 20 07][19 57]	Good	Perfect! NO PROBLEMS!
color[2012 21 07][07 04]	Overall Good	Major background over subtraction in 4 containers
color[2012 21 07][08 33]	Overall Good	background over subtraction in 3 containers
color[2012 21 07][09 33]	Overall Good	Major background over subtraction in 3 containers

Table F.4 : Cont.

Train	Verdict	Comments
color[2012 21 07][09 48]	Good	Perfect! NO PROBLEMS!; All blue containers passed!
color[2012 21 07][10 00]	Overall Good	Major background over subtraction in 4 containers
color[2012 21 07][12 49]	Good	background over subtraction in 1 single stack container
color[2012 21 07][13 03]	Overall Good	background over subtraction in 3 containers
color[2012 21 07][13 30]	Overall Good	Minor background over subtraction in white containers
color[2012 21 07][17 53]	Good	Perfect! NO PROBLEMS!
color[2012 21 07][18 55]	Overall Good	background over subtraction in some single stack containers
color[2012 21 07][19 12]	Bad	background over subtraction in several containers
color[2012 21 07][20 25]	Good	Perfect! NO PROBLEMS!
color[2012 22 07][07 03]	Good	background over subtraction in 3 containers
color[2012 22 07][09 24]	Good	minor background over subtraction in 1 white container
color[2012 22 07][09 38]	Good	Perfect! NO PROBLEMS!
color[2012 22 07][10 25]	Good	Perfect! NO PROBLEMS!
color[2012 22 07][13 06]	Good	Perfect! NO PROBLEMS!; All blue containers passed!
color[2012 22 07][13 49]	Good	Perfect! NO PROBLEMS!
color[2012 22 07][15 03]	Good	Perfect! NO PROBLEMS!
color[2012 22 07][15 33]	Overall Good	Major background over subtraction in 4 white containers
color[2012 22 07][16 26]	Good	Perfect! NO PROBLEMS!
color[2012 22 07][18 18]	Good	background over subtraction in 2 single stack containers
color[2012 22 07][18 50]	Overall Good	background over subtraction in most single stack containers
color[2012 22 07][19 54]	Overall Good	background over subtraction in 1 single stack container; minor background over subtraction in few trailers
color[2012 22 07][20 12]	Bad	background over subtraction in several containers
color[2012 23 07][09 30]	Good	minor background over subtraction in 2 containers
color[2012 23 07][09 41]	Overall Good	minor background over subtraction in few containers; major background over subtraction in 2 containers
color[2012 23 07][15 09]	Overall Good	major background over subtraction in 3 containers; minor background over subtraction in few containers
color[2012 23 07][19 12]	Overall Good	major background over subtraction in 5 containers
color[2012 23 07][19 25]	Overall Good	background over subtraction in single stack containers
color[2012 23 07][20 11]	Overall Good	background over subtraction in few single stack containers
color[2012 24 07][09 05]	Good	Perfect! NO PROBLEMS!
color[2012 24 07][10 15]	Good	background over subtraction in 2 single stack containers
color[2012 24 07][10 43]	Good	background over subtraction in 2 single stack containers; All blue containers passed
color[2012 24 07][13 26]	Overall Good	minor background over subtraction in few white containers
color[2012 24 07][16 44]	Good	Perfect! NO PROBLEMS!

Table F.4 : Cont.

Train	Verdict	Comments
color[2012 24 07][19 32]	Good	Perfect! NO PROBLEMS!
color[2012 24 07][19 46]	Good	Perfect! NO PROBLEMS!
color[2012 24 07][20 01]	Good	background over subtraction in 1 container

APPENDIX G

MATLAB CODE FOR CONVERTING AN IMAGE TO AN INTENSITY MAP IMAGE

The following MATLAB code is used to compute the average convert an image to an intensity map Image.

```
function map(img, filename, bins);
%intensity map of image

img = rgb2gray(img);

intensityMap = zeros(size(img));
[r c] = size(img);

for row =1:r
     for col =1:c
          for k =1:bins
               lowerLimit = ((k-1)*256)/bins;
               upperLimit = (k*256)/bins;
               if(lowerLimit <= img(row,col) && img(row,col) < upperLimit)
                    intensityMap(row,col) = lowerLimit;
               end
          end
     end
end
end
```

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